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REVIEW

Advances, Challenges, and Future Perspectives in Surface Water Quality Monitoring Using Remote Sensing and GIS: A Structured Literature Review

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ABSTRACT: Surface water quality is a sensitive global environmental issue, as it is important for long-term economic development and environmental sustainability. Due to population growth, urbanization, and the effects of climate change, the degradation of surface water quality cannot be avoided. Therefore, a more accurate, continuous, and operational monitoring of water quality is highly significant. This study aims to systematically review and synthesize existing literature on the technological advancement, challenges, and future directions of Remote Sensing (RS) and Geographic Information System (GIS) techniques in surface water quality monitoring. Following PRISMA guidelines, a structured literature search of published studies was conducted across Science Direct, Web of Science, and Scopus databases between 2012 and 2025. The findings demonstrate that RS data can reliably retrieve key water quality parameters and provide large-scale, repeatable observations across surface water when integrated with GIS-based spatial modeling and *in situ* validation. This review systematically consolidates RS retrieval methods and GIS-based analytical frameworks, explicitly distinguishing robust retrievals from context-dependent proxy approaches and identifying methodological gaps that constrain operational deployment. The synthesis from the integration of the enhanced RS–GIS results will enable the RS–GIS community to develop a strong, scalable pathway to map spatial heterogeneity and future-ready water quality monitoring systems that support environmental sustainability, resource security across diverse aquatic environments, provide early warning on environmental risks, and inform water governance.

KEYWORDS: Remote sensing; GIS; water quality; surface water; machine learning

1 Introduction

Access to reliable freshwater supplies strengthens human health, underpins economic development, and supports the sustainability of natural ecosystems [1,2]. However, as global populations continue to rise and urbanization accelerates, pressures on freshwater systems intensify, leading to an increasing degradation of water quality. This decline poses serious risks to public health and threatens the ecological stability [3,4]. As the quality and availability of freshwater resources have become a pressing issue globally [5,6], water quality monitoring is necessary, particularly in water resource management. Timely identification of emerging problems through the trend analysis in water quality provides fundamental information for advanced management strategies [7,8]. To date, there has been a significant water quality assessment and prediction, which enables the understanding of spatiotemporal water quality dynamics and provides scientific support for aquatic environmental protection.

Water quality monitoring is traditionally done manually, collecting water samples from various sources of water and analyzing them under controlled laboratory conditions. The samples are analyzed for their physicochemical and biological parameters that affect the water quality [9]. However, given that this method is considered accurate, it is time-intensive and requires human expertise, equipped laboratory facilities, and a considerable amount of investment during extensive field work for data collection. Additionally, due to the time required for field sampling and laboratory analysis, it is not possible to get immediate results to respond to water pollution emergencies, thereby increasing the risk of environmental hazards [10]. Some of the traditional water quality monitoring approaches are: (1) on-site sample collection with lab analysis; (2) rapid on-site testing; and (3) automatic monitoring stations [11].

Although continuous monitoring of water sources in real-time water quality assessment offers numerous advantages, it is also impractical with the traditional methods [12], as a standalone solution for large-scale or long-term use. Some of the drawbacks of continuous water quality monitoring in real time are the initial cost of installation and maintenance due to the substantial price of specialized sensors, often calibration and cleaning for accurate and reliable data, and challenging interpretation due to the complexity of data management and analysis. From the challenges and limitations of using traditional water quality monitoring approaches, advances and innovations are highly significant, such as satellite-based remote sensing, machine-learning and data-driven models, integration of remote sensing with GIS, and complementary use of *in-situ* sensor networks and telemetry.

Remote sensing technology appears as a promising solution, which offers a time-efficient and large-scale monitoring capacity [13] and an effective approach to efforts and cost reduction [8] that complement traditional methods. It is also a solution in providing data that can be used for environmental management, research, and policy decisions.

Moderate to coarse spatial resolution of remotely sensed data from satellite imagery has been effectively shown to produce promising results in monitoring water quality in inland water bodies [14–16]. More recently, Unmanned Aerial Vehicles (UAVs) RS has drawn growing interest in scientific researchers and industry, due to its broad application predictions, such as in agriculture, forestry, mining, and other industries. UAVs can be flexibly provided with various sensors, such as optical, infrared, and Light Detection and Ranging (LiDAR), and have become an integral RS observation platform [17]. When a UAV is equipped with sensors with RS capabilities, it has the flexibility to collect information against exclusive reference while subject to remote human control. On the other hand, when the RS sensors were enhanced, the performance of the remote-control technology also improved. RS equipment compatibility was increased, the RS data reception and processing capabilities were developed, and UAV platforms and sensors became integrated, which gradually led to the development of RS applications with new capabilities [18].

One of the new capability of RS technology are Machine Learning (ML) techniques, which are capable of identifying the incremental patterns and trends that may be overlooked in traditional methods and making it remarkably advantageous in handling complex RS data [19,20]. Notwithstanding these advantages, there are still challenges in selecting the most effective ML algorithms for monitoring models and ensuring the reproducibility of analysis [21]. With the rapid advancement in the field of RS and the increasing availability of satellite data in the open domain, researchers are leveraging this data for water quality monitoring.

Another platform that incorporates spatial data, environmental variables, and RS outputs is the use of GIS. This is a broadly used tool for evaluating water quality and quantity. For example, the application of GIS techniques and Water Quality Index (WQI) in the assessment of water quality in the context of reservoir systems revealed to be a valuable contribution statistically to the understanding and management of connected water bodies [22], evaluation of surface water quality within a GIS framework by characterizing the physio-chemical characteristics of surface water from various locations [23]. GIS has developed rapidly to become efficient computing tool for various applications such as sophisticated 3D analyses and modeling [20], mapping the distribution of water quality parameters for identification of contamination hotspots [24], and predicting WQI values in unsampled areas to enhance the spatial coverage and enabling proactive decision-making in regions where direct water quality measurements are limited [25]. The WQI is a widely adopted tool for synthesizing various physical, chemical, and biological parameters into a single value that facilitates interpretation and decision-making [26]. When combined with GIS, WQI allows a spatial and temporal mapping of water quality and improved environmental assessments using methodologies such as statistical modeling and ML [27]. For instance, WQI was integrated with the GIS to spatially visualize and examine water quality data to identify the pollution hotspots, trend analysis for effective water resource management [28]. In response, the advances in RS and GIS technology offer an opportunity to demonstrate a better understanding to contribute to watershed management, pollution source identification, and environmental planning.

This paper aims to identify the critical gap by synthesizing recent advances in surface water quality monitoring using RS and GIS techniques and identifying future research opportunities and implementation challenges. This review compares the traditional water quality monitoring approaches with emerging RS data and GIS as a decision support tool. It further covers the fundamentals of RS for water quality, types of sensors, water quality parameters, retrieval algorithms, and analytical methods. Finally, this review consolidates the advances, challenges, and limitations to inform the development of current operational monitoring systems that support transparent, adaptive, and knowledge-based water resource decision-making.

2 Methods

This review was conducted in accordance with the PRISMA [29] guidelines to ensure transparency, reproducibility, and methodological rigor at each stage of the review process. The PRISMA checklist informed the procedures for study identification, screening, eligibility, and final inclusion (shown in Fig. 1). This structured approach helped reduce potential sources of bias and enabled reliable synthesis.

2.1 Identification

A systematic search was conducted across three major scholarly databases, namely ScienceDirect, Scopus, and Web of Science (WoS), to identify studies relevant to this review. These databases were chosen to cover a wide range of scientific publications. This allowed comprehensive retrieval of relevant studies. The search included only articles published from 2012 through 2025. The research strategy employed a rigorously designed Boolean expression: ("water quality monitoring" AND "remote sensing"), ("water quality monitoring" AND "GIS"), ("water quality monitoring" AND "remote sensing" OR "machine learning"), ("surface water" AND "remote sensing" AND "GIS") were used to refine the search, and duplicate records were removed using a reference manager.

2.2 Screening

In the screening stage, records were assessed based on titles and abstracts using explicit eligibility criteria. A total of 287 records were retrieved from ScienceDirect, Scopus, and Web of Science (WoS) and other sources (i.e., official websites and conference papers). After removing 29 duplicates, 258 records remained for screening. Of these, 105 records were excluded after title and abstract screening. 153 articles underwent full-text assessment, and 50 were removed because they were irrelevant or did not meet the eligibility criteria such as, (i) studies focused on domains outside the review scope (groundwater monitoring systems, land-only environmental monitoring, and marine ecological assessments without water quality parameter retrieval), (ii) absence of empirical application, and (iii) editorials or opinion papers. Ultimately, 103 studies were included in the final synthesis.

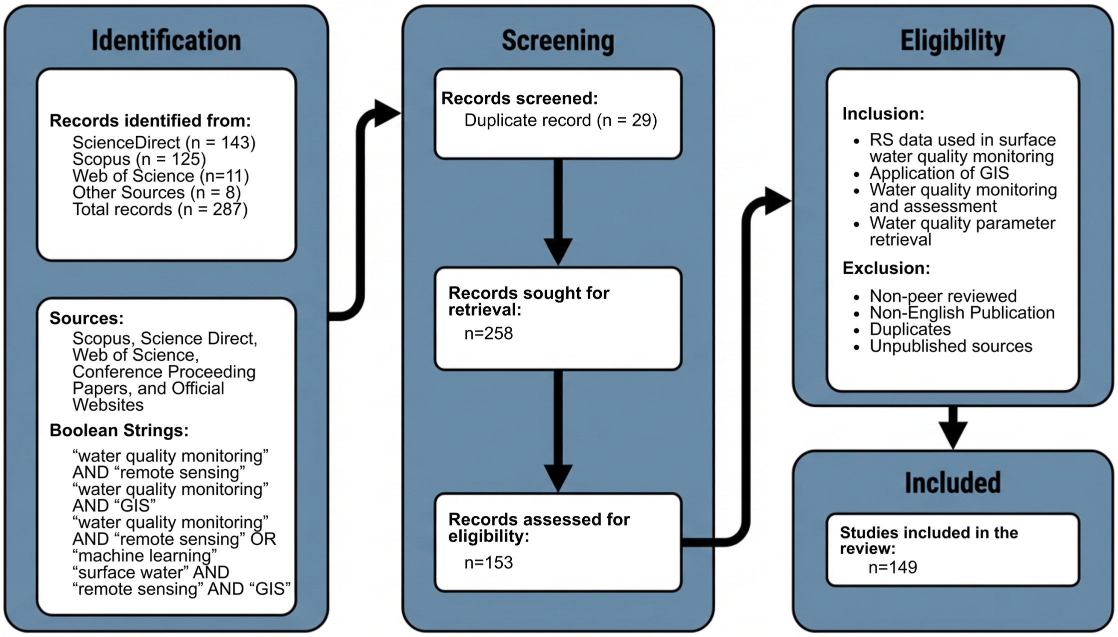

Figure 1: The diagram presents the structured literature review methodology used to identify and select studies on the advances, challenges, and future perspectives in surface water quality monitoring using RS and GIS.

2.2.1 Data Extraction

The study was conducted using a standardized data collection form designed to obtain the most relevant information from each included study. The extracted data included key attributes (authors, year, study area), methodology, and major findings. To ensure accuracy and consistency, data from each included study were extracted individually by two reviewers, with no automation tools employed in the data extraction process.

2.2.2 Data Items

The initial outcomes of this review were the water quality parameters retrieved using RS and GIS techniques, and the methodological approaches used for estimation. Specifically, the methodological outcomes were extracted from the types of remote sensing platforms and sensors, retrieval algorithms, validations, and model performance. All relevant results for each, including study on the initial outcomes were collected.

In addition to the initial outcomes, other variables were extracted to maintain the contextual and methodological interpretation of the included studies. These include publication details, geographical setting, type of water body, and classification of study regions. There were no assumptions made about missing or unclear data, and only explicitly reported results were included in the synthesis.

2.3 Eligibility

The inclusion criteria for this review required that studies explicitly applied or discussed RS and GIS within the context of water quality monitoring, covering domains such as surface water quality monitoring and assessment, and applications related to water quality parameter retrieval. Only peer-reviewed journals and conference proceedings articles written in English and presenting clear methodological frameworks, validation strategies, or empirical findings were considered eligible. To maintain academic rigor and ensure the reliability of synthesis, unpublished sources were excluded from the analysis. Duplicate records identified across databases were removed using reference management software, followed by manual verification.

2.4 Final Inclusion

Following the full screening and eligibility assessment, a total of 103 studies met all inclusion criteria and were included in the final synthesis. These studies represent the most relevant and methodologically robust peer-reviewed evidence on the application of remote sensing and GIS in water quality monitoring within the defined scope of this review. This final inclusion ensured that the review was based on studies with clear methodological transparency and direct relevance to water quality monitoring and assessment. Additional references were retained to support background information, methodological explanations, and interpretation of findings.

2.5 Effect Measures

There is no quantitative effect measure used in this review since the findings were synthesized qualitatively. Instead, study findings were presented descriptively, which focused on the methodological approaches, retrieved water quality parameters, and reported model performance.

2.6 Synthesis Process

Studies were grouped for synthesis based on thematic and methodological characteristics, including: (i) traditional monitoring approach vs. RS technologies, (ii) remote sensing systems and observation platforms, (iii) water quality parameter types, (iv) retrieval methods, and (v) GIS Integration in water quality monitoring. Extracted data were classified according to the parameters and methods into consistent categories. Missing data were not cited, and only clearly reported results were included.

A qualitative narrative synthesis was conducted due to methodological heterogeneity among studies, and the results were presented using narrative summary tables with the key study characteristics, identifying patterns, methodological trends, strengths, limitations, and research gaps across studies. Variability was explored through subgroup analysis based on sensors, platforms, water bodies, and methods. No formal sensitivity analysis was conducted due to the qualitative nature of the synthesis and the absence of comparable quantitative effect measures. However, a greater weight was given to studies with strong validation strategies and larger datasets to support reliable interpretation of findings.

2.7 Risk of Bias Assessment

To ensure the robustness and credibility of the synthesized evidence, a qualitative risk of bias assessment was conducted for all included studies. Due to the methodological diversity of RS and GIS-based water quality research, a framework was developed based on commonly reported methodological limitations in the literature. Each included study was independently evaluated by two reviewers, and no automation tools were used in the risk of bias assessment process.

The assessment considered five key criteria: (i) quality of input data; (ii) validation strategies; (iii) model transparency and reproducibility; (iv) confounding factors; and (v) generalizability of results. Each study was qualitatively evaluated based on criteria and categorized as having low, moderate, or high risk of bias. This assessment was conducted during the data extraction phase and was used to inform the interpretation of findings, particularly in identifying methodological limitations and research gaps across the reviewed literature.

3 Results

To provide a general overview of the articles reviewed, Table S1 presents a summary of reviewed studies according to key attributes such as authors, year, methodology, study region, and major findings. Most studies focus on satellite-based monitoring of optically active parameters, while an increasing number incorporate machine learning and multi-sensor integration.

This section includes the studies focusing on groundwater monitoring systems, land-only environmental assessments, or marine ecological analyses without clear water quality parameter retrieval, which were excluded, as they did not align with the scope of this review. Additionally, studies without sufficient empirical application, such as conceptual frameworks, editorials, and opinion-based articles, were excluded due to the absence of methodological validation or quantitative results.

The risk of bias assessment, shown in Table S2, indicates that studies with strong validation strategies, sufficient *in situ* data, and transparent methodologies provide higher confidence, whereas studies relying on limited datasets or site-specific calibration exhibit greater methodological limitations. Due to substantial heterogeneity in study designs, data sources, and analytical approaches, no quantitative meta-analysis was conducted, and the synthesis was performed qualitatively. The regional distribution of selected studies was categorized as developed and developing countries based on World Bank [30] income classifications, which is also provided in Table S3 and Fig. S1.

Meta-analysis was not conducted in this review due to significant heterogeneity among the included studies in terms of data sources, remote sensing platforms, water quality parameters, and analytical methods.

As a result, summary effect estimates, confidence intervals, and measures of statistical heterogeneity were not calculated. Instead, findings were synthesized using a qualitative narrative approach to identify patterns, trends, and methodological differences across studies.

3.1 Traditional Monitoring Approach vs. Remote Sensing Technologies

The reviewed literature reveals two primary monitoring approaches: traditional ground-based techniques or field sampling methods and RS-enabled spatial monitoring frameworks. Shifting from traditional monitoring to RS technology does not position itself as a basic technological replacement but as a strategic adaptation to the identified spatiotemporal limitations in traditional systems.

Across the synthesized literature, it was evident that the identified limitations of traditional monitoring are that although laboratory-based analyses and *in-situ* sampling provide high analytical precision, it is labor-intensive, costly, and operationally constrained [31,32]. Likewise, the spatiotemporal variability in surface water bodies such as rivers, lakes, and reservoirs shows constraints due to the sampling or data collection conducted in fixed locations and discontinuous time intervals [33,34], and the limited accessibility to remote sites further restricts their spatial coverage [35]. The synthesis indicates that these framework limitations often produce spatiotemporal gaps, during which occasional pollution events or localized degradation may remain undetected [16]. These recurring observations in the literature have driven increasing research interest in monitoring approaches capable of broader spatial coverage and higher temporal frequency [36]. In response to these identified gaps, RS has increasingly become a methodological direction within the reviewed studies. RS-based approaches are consistently highlighted for their ability to provide a broad range of repeatable observations across a larger scale without requiring physical site access [15,37]. It can track trends using satellites and aerial platforms for data collection, and offers a valuable perspective for investigating different region types and emphasizes that satellite and airborne platforms improve the illustration of spatial patterns and temporal dynamics in water quality parameters, particularly in systems where manual sampling is sparse [38].

The literature further illustrates the broad application of multispectral sensors, such as Landsat, Sentinel, MODIS, MERIS, etc., for inland and coastal water quality monitoring. Behind the relatively high revisit frequency and accuracy for optically active parameters, these platforms still show continual challenges, including optical complexity in inland waters, atmospheric correction uncertainty, and sensor resolution constraints [11]. Hence, while RS expands its monitoring scope, its application requires thorough algorithm selection, calibration, and validation.

The reviewed studies also report an increasing interest in active and near-proximal platforms such as solar illumination, LiDAR, and Synthetic Aperture Radar (SAR), which generate their own signals, enabling additional structural and hydrological information [39]. More recently, unmanned aerial vehicles (UAVs) and unmanned surface vehicles (USVs) have been increasingly implemented for high-resolution and local-scale monitoring [40,41]. It shows that UAV-based hyperspectral and multispectral imagery, with the integration of machine-learning models, yields a high retrieval accuracy for turbidity, TN, TP, and Chl-a in rivers and small inland water bodies [42–44]. However, it was also reported that UAV-derived models are often site-specific, constrained by limited spatial extent and temporal continuity, and are less effective for capturing rapid hydrological fluctuations at broader scales. Accordingly, existing studies join in suggesting that UAV–RS integration is most effective as a complementary element in monitoring frameworks rather than deployed as a standalone solution for large-scale or long-term applications.

The analyzed studies illustrate a clear methodological transition: from ground-based and labor-intensive monitoring toward multi-scale, sensor-integrated systems designed to improve spatiotemporal representativeness in surface water quality monitoring.

3.2 Remote Sensing in Water Quality Monitoring

RS System Categories and Observation Platforms

The RS systems applied in water quality monitoring can be systematically categorized according to energy sources and observation mode: (i) Passive RS systems that uses the sun as the source of light and therefore can operate only during the daytime [45]; (ii) active RS and Near-Real-Time Monitoring System that uses their own energy and can operate during both day and night; and (iii) system observation platforms. Table 1 presents a summary of active and passive remote sensors and platforms for surface water quality monitoring, and their strengths and limitations.

Table 1: Summary of active and passive remote sensing sensors and platforms for surface water quality monitoring: strengths and limitations.

Sensor/Platform Type	Examples	Key Strengths	Key Limitations
Passive Sensors			
Multispectral satellites (medium resolution)	Landsat-8/9 OLI, Sentinel-2 MSI, MODIS	• Robust retrieval of optically active parameters • Long-term, consistent archives enable trend analysis • Relatively good transferability for optical variables	• Limited capability for optically inactive parameters • Affected by AC, adjacency effects, and cloud cover • Moderate spatial resolution limits narrow rivers and small lakes

(Continued)

Table 1 (continued)

Sensor/Platform Type	Examples	Key Strengths	Key Limitations
Ocean-color satellites (coarse resolution)	MODIS, Sentinel-3 OLCI, MERIS	• Physics-based and semi-analytical algorithms • Regional to global consistency • Effective for Chl-a, CDOM, turbidity, and climate-scale assessments	• Coarse spatial resolution • Reduced applicability in small inland waters and nearshore zones • Complex optical waters reduce accuracy
High-resolution commercial satellites	PlanetScope, Worldview	• High spatial detail for small and fragmented water bodies • Improved detection of spatial heterogeneity	• Limited spectral bands; higher cost • Retrieval is often empirical and site-specific • Reduced transferability
Airborne hyperspectral sensors	CASI, AVIRIS, HyMap	• High spectral resolution supports mechanistic retrieval and algorithm development. • Strong for optically active parameters	• High cost • Limited spatial and temporal coverage • Not operational for routine monitoring
Thermal infrared sensors	Landsat TIRS, MODIS TIR	• Reliable surface water temperature retrieval • Supports stratification and DO proxy analysis	• Surface-only information • Cloud sensitivity • Coarse resolution for some platforms
		Active Sensors and NRTM	
LiDAR-based	Bathymetric LiDAR, fluorescence LiDAR	• Vertical profiling of water columns • Reduced dependence on solar illumination • Enhances calibration of passive RS	• High operational cost • Limited spatial coverage • Complex data processing
Radar and microwave sensors	SAR, radar altimeters	• All-weather, day-night capability • Water extent, level, and surface roughness monitoring • Complements optical RS	• Limited direct sensitivity to water-quality parameters • Indirect relevance
Near-real-time monitoring	*In-situ* sensor networks, telemetry systems	• Direct measurement of DO, pH, and conductivity • High temporal resolution • Essential for calibration and validation	• Point-based measurements • Limited spatial representativeness • Maintenance-intensive

(Continued)

Table 1 (continued)

Sensor/Platform Type	Examples	Key Strengths	Key Limitations
Observation Platforms			
Satellite platforms	Multispectral, hyperspectral, thermal, and radar	• Large-scale, repeatable coverage • Long-term monitoring • Suitable for basin to global assessments	• Fixed overpass times • Cloud contamination • Spatial resolution constraints
Unmanned Aerial Vehicles (UAVs)	RGB, multispectral, hyperspectral	• Ultra-high spatial resolution • Effective for local-scale monitoring and validation	• Limited spatial extent and temporal continuity • Site-specific results
Unmanned Surface Vehicles (USVs)	*In-situ* sensors, optical probes	• Dense spatial sampling • Improved coverage over traditional point sampling	• Limited operational range • Weather-dependent
Proximal sensing systems	Fixed or mobile hyperspectral sensors	• High-frequency observations • Strong support for process studies and early warning	• Very limited spatial coverage • Low transferability
Integrated multi-platform systems	RS + UAV + *in-situ* sensors	• Improved spatiotemporal resolution • Reduced uncertainty • Stronger validation	• Increased complexity • Harmonization challenges • Higher data requirements

Passive RS System

The reviewed studies demonstrate that medium-resolution multispectral satellites play a central supporting role in inland and coastal water-quality monitoring. Optically active RS systems exploit visible–NIR bands and band ratios to directly retrieve optically active parameters, particularly Chl-a, turbidity, and TSS. Conversely, chemically and biologically optically inactive parameters such as nutrients (TP and TN), DO, BOD, COD, and salinity, are indirectly inferred or proxy-based, which are calibrated with *in-situ* data and, in many cases, refined using machine-learning (ML) algorithms. For instance, Sentinel-2 MSI was used to retrieve multiple water-quality parameters—DO, CODMn, NH_3-N, TP, TN, and turbidity—in the Yangtze River Delta; one-dimensional regression on NIR bands achieved sufficiently high inversion accuracies to demonstrate the feasibility of routine concentration mapping from MSI reflectance [46]. Similarly, Landsat-8 OLI data were coupled with LASSO regression and spectral indices to predict temperature, TDS, pH, turbidity, Chl-a, DO, and blue-green algae in the Tigris River; the model provided a cost-effective alternative to dense field sampling and enabled computation of a WQI that revealed persistently poor water quality [47,48]. Several studies highlight the strength of band-combination regression for single parameters. For example, in Lake Tana, ordinary least-squares models using specific Landsat-8 bands explained ~87% of turbidity variance, demonstrating that simple linear models on carefully chosen bands can be robust for sediment-rich waters [49]. Likewise, empirical band-ratio models from Sentinel-2 (ratios such as B5/B4, B4/B3, and B4) effectively mapped spatiotemporal patterns of Chl-a, turbidity, and TSS in the Koka Reservoir, supporting diagnosis of eutrophication and shallow-water sediment dynamics [50]. Overall, medium-resolution multispectral satellites perform best in medium-to-large rivers, lakes, reservoirs, and sediment-rich water. It consistently permits repeatable retrieval of optically active water-quality parameters at regional scales. However, these satellite estimates on optically inactive parameters as proxy-based are sensitive to calibration density, AC, and water-type variability, which indicates the need for further strategies.

A large cluster of studies further shows that combining Landsat and Sentinel-2 with advanced machine-learning algorithms greatly improves retrieval accuracy and allows multi-parameter prediction. For instance, RF, XGBoost, support-vector regression, and deep neural networks applied to Landsat/Sentinel-2 reflectance achieved high R^2 for turbidity [51], TSS [52,53], Chl-a [54,55], nutrients such as TN and TP [56–58], and algal bloom [59] in rivers, lakes, and coastal waters, often outperforming classical semi-analytical algorithms. In these works, the major strengths are high predictive power (often $R^2 > 0.8$), ability to handle multi-parameter datasets, and explicit mapping of spatiotemporal pollution patterns such as eutrophication hot spots, urban plume zones, and seasonal turbidity peaks. ML-based multispectral retrieval works well for multi-parameter mapping in rivers, lakes, and reservoirs with sufficient *in-situ* training data by capturing nonlinear spectral relationships, but performance degrades outside calibration domains, highlighting the need for spatial–temporal cross-validation and transferable model design.

Finally, some studies leveraged very large archives of Landsat reflectance to model TSS, TN, TP, DO, and Chl-a across many rivers, revealing continental-scale patterns and demonstrating that neural-network models trained on long time series can robustly generalize across diverse hydrological conditions [52,60–63]. While the key strength of passive multispectral RS obtains multi-decadal, spatially continuous records of inland water quality, it is most effective when used for large scales, such as large lakes, major river basins, and coastal waters. This demonstrates the unique strength of passive RS in resolving long-term and large-scale water-quality trends. However, when a need arises for a short-term or local scale, higher-frequency observations are still needed.

A second major group uses ocean-color sensors and other coarse-resolution passive instruments to monitor regional to global patterns of phytoplankton biomass, CDOM, nutrients, and related biogeochemical indicators. For instance, MERIS and Sentinel-3 OLCI products, often processed with C2RCC, MPH, and quasi-analytical algorithms, were shown to retrieve Chl-a, Secchi depth, and turbidity with overall regressions close to 1:1 relative to *in-situ* data across >100 German lakes, confirming their value for national-scale monitoring [64–66]. Similarly, long-term products such as MYDOCGA-MODIS reflectance were used with XGBoost to map TN and TP in Hong Kong's coastal waters, revealing both hot spots (e.g., Shenzhen Bay) and decadal declines in nutrient levels, thereby showcasing the strength of ocean-color time series for tracking long-term management outcomes [67]. Ocean-color sensors are best suited to open coastal waters and large lakes with medium to large scales. It substantially performs in homogeneous conditions but performs poorly on a smaller scale due to the coarse resolution. Therefore, these constraints required downscaling or complementary higher-resolution sensors for small inland waters. This is further proven when [68] downscaled the 20-m resolution SWIR band from Sentinel-2 images to 10 m based on pan-sharpening, which shows a more detailed spatial information of water bodies. Also, ref [69] highlights that comprehensive water data listing remains insufficient, especially for small water bodies, such as ponds, which are overlooked regardless of their ecological significance.

Other studies compared different processing chains and products—for example, JAXA G-Portal vs. JASMES GCOM-C/SGLI retrievals—showing that multi-product ensembles can reduce uncertainty in Chl-a and TSM estimates, while still providing globally consistent coverage [70–73]. In coastal and estuarine seas, products from MODIS, VIIRS, COCTS, and GOCI, combined with empirical, semi-analytical, and ML algorithms, proved particularly effective for harmful algal bloom (HAB) monitoring and deoxygenation assessments, for instance, detecting cyanobacterial blooms in Lake Erie and summer coastal deoxygenation associated with reclamation projects [71,74–77]. Some contributions extended this to global biogeochemical indicators, such as remote retrieval of sea-surface nitrate trends from MODIS, demonstrating decreasing SSN linked to global warming and ENSO variability [78], or to lake climate-product evaluation, where CLMS/ESA lake products showed robust LSWT retrievals and usable Chl-a and turbidity information at the continental scale [79]. The advantages of coarse-resolution passive missions have been evident in providing long, consistent, and often near-global coverage needed to understand climate-scale and basin-scale water-quality change.

A third cluster in the review literature emphasizes high-spatial or high-spectral-resolution passive sensors for local-scale, detailed water-quality assessment. For example, in the study of Di Francesco et al. [8], PlanetScope microsatellites and Sentinel-2 were shown to accurately retrieve Chl-a, turbidity, and cyanobacteria in small lakes using semi-empirical indices and ACOLITE processing, demonstrating the cost-effective potential of daily microsatellite constellations for near-real-time water-quality mapping. Coccia et al. and Lei et al. [80,81] at even finer scales, airborne hyperspectral sensors such as CASI-1500 and AMMIS enabled precise mapping of pond depth, turbidity, Chl-a, TN, and TP, distinguishing restoration success and identifying algal-bloom-affected shorelines that would be missed by coarser sensors. These high-resolution commercial satellites are effective for small lakes and urban rivers, and they enhance the detection of fine-scale optical variability. However, resolving the finer spatial scales of these satellites also became their limitations due to the limited coverage, cost, and operational constraints, which restrict deploying on a larger scale.

Proximal hyperspectral systems (HPSs) were also deployed over lake surfaces to retrieve ultra-high-frequency lake surface temperature and related thermal dynamics via ML models such as XGBoost, DNN, and KNN, providing an effective early-warning tool for harmful algal bloom risk and heatwave-driven stratification disruption [82]. The key strength of these high-resolution passive systems is therefore their ability to resolve fine-scale heterogeneity in shallow, small, or complex water bodies and to support intensive local management and restoration actions. However, it is limited to spatial representativeness, which necessitates integration with satellite or UAV observations for broader applicability.

A final set of passive-sensor studies in the reviewed studies emphasizes data fusion and multi-sensor integration to leverage complementary strengths. For example, an advanced spatiotemporal fusion model (ESTARFM) combined Landsat-8 OLI and MODIS to generate higher-frequency SPM maps with improved accuracy compared to alternative fusion methods, showcasing how fusion can yield both high spatial and temporal resolution for sediment monitoring [83]. Similarly, Sentinel-2 and Sentinel-3 imagery were integrated to derive harmonized Chl-a products and uncertainty fields via Bayesian neural networks and mixture density networks, enabling consistent cyanoHAB monitoring across sensor platforms and supporting public-health risk management [84]. Multi-mission constellations (e.g., GF-1, Landsat-8, Sentinel-2) combined through genetic-algorithm-optimized RF were also shown to give superior TN/TP retrievals compared with single-sensor models [43,85–87]. Using data fusion and multiple sensors performs best across heterogeneous waters and cloudy regions by combining the spatial and temporal strengths of different sensors, although it increases the methodological complexity.

Together, these studies highlight that passive techniques are strongest when they exploit multi-sensor synergies, providing: (i) higher revisit frequency, (ii) better handling of cloud gaps, and (iii) improved robustness of inversion models across varying optical regimes.

Active RS and Near-Real-Time Monitoring System

Throughout this review, the term active remote sensing is taken for radiometric systems, whereas *in-situ* telemetry and RTRM systems are discussed as near-real-time monitoring systems that complement, but do not replace, remote sensing observations.

Among the active systems, LiDAR-based techniques stand out for their ability to probe the vertical dimension of the water column. For instance, shipborne lidar using the Fernald method successfully retrieved Chl-a and optical properties in Qiandao Lake, with findings indicating that LiDAR has strong potential for long-term monitoring of inland lakes and that the proposed retrieval could be transferred to other sites [88]. In another study, marine LiDAR with laser-induced fluorescence was combined with Sentinel-2 MSI to estimate Chl-a, CDOM, and TSS. Regional bio-optical models derived from these active–passive combinations showed good applicability across both eutrophic and oligotrophic waters, demonstrating that LiDAR can sharpen satellite-derived bio-optical algorithms and extend them to optically diverse conditions [89]. These LiDAR applications illustrate the main strength of active optical systems. It provides vertically resolved, highly sensitive measurements of water constituents, which can be used both for direct monitoring and for calibrating passive satellite algorithms in complex waters. Yet, LiDAR performs best in optically complex lakes and reservoirs; there are still limitations that may be improved, such as high operational costs and limited coverage, which restrict its use to calibration, validation, and process studies.

Another set of active techniques involves satellite radar altimeters and associated microwave missions, often used in combination with optical imagers. For example, multi-mission radar altimetry (TOPEX/Poseidon, ERS-2, Envisat, CryoSat-2, SARAL) combined with Sentinel-3 OLCI observations were used to assess trends in lake water level, Chl-a, and turbidity. Boosted regression trees showed that increases in Chl-a were strongly linked to catchment built-up area and shrinking water surface, underscoring the strength of altimeter–ocean-color synergies for diagnosing land-use impacts and climate-driven hydrological change [90]. Microwave and thermal IR data were also used to infer DO and related variables at coastal scales; for instance, MODIS and VIIRS products, together with SST and Chl-a, allowed multiple regression models to detect significant summer deoxygenation associated with reclamation projects in the Yellow Sea [75], while other MODIS-based work retrieved global sea-surface nitrate trends [78]. These demonstrate that active microwave missions, though less frequently used than optical sensors, add unique information on water level, circulation, and large-scale nutrient dynamics that are difficult to obtain from passive visible–NIR data alone. Commonly, radar and microwave missions are most effective in large lakes, flood plains, and coastal waters for water level and surface dynamics; however, their weak sensitivity to water-quality constituents limits direct WQP retrieval, emphasizing their complementary role.

In addition, this review also includes real-time remote monitoring (RTRM) systems, which are essentially active *in-situ* sensor networks sending data remotely rather than remote-sensing in the classical radiometric sense. For instance, RTRM installations measuring DO, pH, conductivity, turbidity, and sediment concentration in marine waters were interpreted with fuzzy systems and neural networks to characterize the spatial vulnerability of coastal zones, identify areas where DO remained supportive of aquatic life, and highlight recreational disturbances from boating [91]. The strength of these systems lies in their high temporal resolution and direct measurement capability, which complements both passive and active satellite observations that are limited by overpass time and atmospheric conditions.

These RTRM and USV/UAV platforms can be viewed as active monitoring technologies that, when combined with satellite and airborne imagery, create multi-scale, multi-sensor observing systems capable of capturing everything from sub-hourly events to multi-decadal trends. For instance, the consistent success of Landsat and Sentinel-2/3 in retrieving Chl-a, turbidity, TSS, DO, and nutrients in very different water bodies—rivers [48,51,92], lakes and reservoirs [46,50,93–96], bays and coasts [85,87,97,98], and open sea/coastal systems [67,71]—is a central strength emphasized in the reviewed studies.

Active techniques (LiDAR, radar altimetry) and near-real time monitoring systems (RTRM networks), while fewer in number, add depth, structural information, and temporal continuity: LiDAR yields vertical profiles of Chl-a and optical properties, strengthening calibration/validation in optically complex lakes [88,89]. Radar altimetry and related missions capture water-level dynamics and large-scale nutrient/temperature changes, enriching interpretations of satellite-observed Chl-a and turbidity [78,90]. Passive optical sensors are the backbone of water-quality RS, while active techniques, near-real time monitoring systems, and unmanned platforms provide critical added strengths, vertical profiling, hydrological context, and real-time local detail, that together form an integrated multi-sensor observing system for surface-water monitoring. Near-real-time monitoring systems work best in managed rivers, lakes, and coastal zones, requiring rapid response by providing direct, high-frequency measurements. Yet, spatial representativeness is being limited due to its point-based nature and maintenance demands, which can be further looked for improvement.

Observation Platforms

Beyond sensor type and energy source, RS performance is also strongly governed by the observation platform on which sensors are deployed.

The reviewed literature also dedicates several entries to unmanned platforms (UAVs and USVs) carrying passive RGB or multispectral cameras, which bridge the gap between *in-situ* measurements and satellites. For instance, drone-based RGB imagery combined with ML models such as RF, GBM, XGB, and KNN accurately predicted *E. coli* concentrations in irrigation ponds, demonstrating that simple RGB indices, when collocated with water-quality samples, can provide high-resolution microbial risk maps for local irrigation management [99]. Similarly, UAV-borne multispectral cameras with indices like NDCI, NDAI, MCI, and CI were combined with satellite imagery and *in-situ* geophysical measurements to map stream-scale algal patches and guide buffer-zone and pollutant-load management [100]. Other UAV-based shows advanced ML architectures (e.g., GA-optimized XGBoost, TLNet, CNN, LSTM, Transformer) accurately retrieving TP, TN, DO, TSS, and Chl-a in small lakes and urban rivers, capturing sharp spatial gradients linked to aquaculture, urbanization, and point sources [43,101]. On the surface, USVs equipped with Chl-a sensors were used to generate spatially interpolated Chl-a maps using Kriging/IDW, showing that autonomous surface vehicles can efficiently collect high-density datasets over streams and reach-scale systems, and the resulting maps are promising for the commercialization of remote monitoring technologies. UAV-based monitoring is most effective in small lakes, narrow rivers, and urban water bodies, which significantly improve local-scale water-quality characterization and satellite validation through ultra-high spatial resolution. However, standardized protocols and satellite integration are needed because it is site-specific, and temporal continuity is limited. Moreover, USVs perform well in rivers and reservoirs, which enhances spatial sampling density and bridges gaps between point measurements and imagery. However, its reduced scalability and weather sensitivity indicate a need for improved calibration and interpolation rather than standalone monitoring.

The strength of these unmanned-platform approaches is flexibility and ultra-high spatial detail: they can be rapidly deployed over small or narrow water bodies where satellite pixels are too coarse, and they provide near-instant feedback for local managers, while still integrating seamlessly into satellite-based frameworks.

These findings reflect variability in monitoring performance across different approaches, which is influenced by spatial coverage, temporal resolution, and methodological approach, highlighting the heterogeneity of the reviewed studies.

3.3 Water Quality Parameter

Water quality is essential for ecosystems, human health, and economic development. Typically, it is defined by its suitability for a specific use, which is determined by optically active parameters (Chl-a, TSS, SDD, CDOM, turbidity, surface water temperature), which directly influence water-leaving radiance and optically inactive parameters (pH, TN, TP, DO, COD, BOD/CD, and salinity), which lack distinct spectral signatures and are therefore indirectly inferred through proxy relationships, auxiliary variables, and site-specific calibration. Across both optically active and inactive water quality parameters, retrieval performance is dependent on the transferability, confounding factors (AC and adjacency effects), and calibration and validation design. Transferability across regions and seasons remains limited unless models are trained on diverse hydro-optical conditions and evaluated using independent spatial–temporal validation schemes. Thus, the atmospheric correction, i.e., the removal of atmospheric effects, is an essential prerequisite for obtaining accurate watercolor information [102]. The adjacency effect is caused by reflected photons from surrounding land targets that are scattered by atmosphere components into the sensor's field of view [103]. This complex phenomenon reduces the contrast between the high-reflectivity (land) and the low-reflectivity (water) surfaces. As a result, scattered photons from the land targets close to the water bodies can distort water spectral reflectance, mainly affecting small water bodies [104]. Additionally, the absence of *in situ* measurements for calibration and validation raises accuracy concerns; the models that have been developed using RS data need to be properly calibrated and validated using *in situ* data [105–107]. Table 2 shows the summary of water quality parameters retrieved using remote sensing, associated sensors, retrieval approaches, limitations, and data requirements.

Table 2: Water quality parameters retrieved using remote sensing, associated sensors, retrieval approaches, limitations, and data requirements.

Parameter Group	Typical Sensors	Typical Retrieval Approaches	Key Limitations	Data Requirements
Optically Active				
Chlorophyll-a	Sentinel-2/3, Landsat-8/9, MODIS, MERIS, Hyperspectral UAV/airborne	Band ratios (OCx, CI), Semi-analytical (QAA, GSM), ML (RF, XGBoost, CatBoost DNN, ANN, BNNs), Empirical Regression	• Algorithm saturation at very high Chl-a • Sensitivity to AC (AC) and adjacency effects • Confounding by CDOM and suspended sediments in optically complex waters • Reduced accuracy in shallow waters due to the bottom reflectance	• Multispectral or hyper-spectral reflectance • High-quality AC • *In-situ* Chl-a samples for calibration/validation • Water-type classification
Turbidity/TSS	Sentinel-2/3, Landsat-8/9, MODIS, PlanetScope, UAV multispectral	Empirical regression (LASSO, SLR), ML (RF, GB, SVR, RR, XGBoost, Decision Tree, DNN, BPNN)	• Nonlinear response and saturation at high sediment loads • Strong dependence on particle size, composition, and mineralogy • Adjacency effects in narrow rivers and reservoirs • Reduced transferability across regions and seasons	• Red–NIR reflectance bands (and ratios) • Concurrent *in-situ* turbidity/TSS measurements • Site-specific or regionally stratified calibration • Ancillary hydrological data (flow, rainfall) improve robustness

(Continued)

Table 2 (continued)

Parameter Group	Typical Sensors	Typical Retrieval Approaches	Key Limitations	Data Requirements
CDOM	Sentinel-2/3 MODIS, Hyperspectral sensors	Semi-analytical models, ML	• Spectral overlap with Chl-a absorption in blue wavelengths • Weaker signals in low-DOC waters • Algorithm sensitivity to AC quality • Limited transferability across different CDOM sources	• Blue–UV sensitive bands or hyperspectral data • *In-situ* CDOM/DOC absorption measurements • Bio-optical parameterization or semi-analytical models • Consistent AC and noise control
SDD	Sentinel-2/3, MODIS	Semi-analytical (QAA), ML (RF, CatBoost, XGBoost, DNN), Empirical Regression	• Indirect retrieval (derived from Chl-a, TSS, CDOM proxies) • Reduced reliability in shallow or bottom-influenced waters • Sensitive to surface conditions • Algorithm performance varies with trophic state	• Multispectral reflectance • *In-situ* SDD observations • Optical water-type stratification • Co-retrieval of Chl-a and TSS improves stability
Surface Water Temperature (thermally active)	Landsat 8/9, MODIS, VIIRS	Empirical regression (LASSO), ML (XGBoost, DNN, KNN)	• Surface-only measurement (no vertical profile) • Cloud contamination and atmospheric water vapor effects • Reduced spatial resolution for some thermal sensors • Diurnal variability not fully captured by polar-orbiting satellites	• Thermal infrared bands • AC for thermal emissivity • *In-situ* temperature for validation • Meteorological data improves modeling
Optically Inactive				
DO	Sentinel-2, Landsat-5/7/8/9, MODIS, VIIRS	ML (RF, CatBoost, ANN, BPNN), temperature, and turbidity proxies	• No direct optical signal • Strong dependence on temperature, mixing, and biological activity • Proxy relationships are site- and season-specific • High reported accuracy often reflects a limited sample size or co-linearity	• Proxy variables (LSWT, Chl-a, turbidity, stratification indicators) • *In-situ* DO for calibration and independent validation • Ancillary meteorological and hydrodynamic data • Spatial–temporal cross-validation is essential

(Continued)

Table 2 (continued)

Parameter Group	Typical Sensors	Typical Retrieval Approaches	Key Limitations	Data Requirements
TN	Sentinel-2/3, Landsat-5/7/8/9, MODIS	Genetic Algorithm, ML (XGBoost, AdaBoost, CatBoost, RF) + spectral indices	• Weak and indirect spectral linkage • Confounded by land use, runoff, and hydrology • High uncertainty at low or extreme concentrations • Limited inter-basin transferability	• Multispectral reflectance + spectral indices • Dense, seasonally representative *in-situ* TN samples • Catchment variables (land use, rainfall) • ML models with an explicit validation strategy
TP	Sentinel-2, Landsat-5/7/8, MODIS	Genetic Algorithm, ML (XGBoost, AdaBoost, CatBoost, RF) multi-sensor fusion	• Indirect association mainly via algal biomass and sediments • Strongly influenced by episodic events • Sensitive to sampling frequency and timing • Often overfit in small datasets	• Reflectance bands linked to Chl-a and TSS • *In-situ* TP measurements across seasons • Multi-sensor or data-fusion approaches improve robustness • Independent spatial validation is recommended
BOD	Landsat-8, Sentinel-2	ML (XGBoost, Decision Tree, RR) with spectral inputs	• No optical signature; entirely proxy-based • A reported very high R^2 often reflects limited datasets or co-variables • Strongly site-specific and non-transferable • Highly sensitive to validation design	• Multispectral reflectance + multiple auxiliary variables (Chl-a, TSS, temperature, land use, meteorology) • Sufficient sample size covering the variability extremes • Independent spatial–temporal validation mandatory • Clear uncertainty reporting
COD	Sentinel-2, MODIS, PlanetScope, UAVs	Genetic Algorithm, ML (CatBoost, RF, Decision Tree, RR, GBR) + CDOM/turbidity proxies	• Indirect inference via CDOM and turbidity • Variable chemical composition across waters • Reduced accuracy in optically complex or coastal waters • Limited mechanistic interpretability	• Reflectance proxies (CDOM, turbidity, red–NIR bands) • *In-situ* COD for calibration • ML or hybrid models with careful feature selection • Site-specific model tuning

(Continued)

Table 2 (continued)

Parameter Group	Typical Sensors	Typical Retrieval Approaches	Key Limitations	Data Requirements
Salinity	Landsat-8, Sentinel-2	ML (RF, GBR, DNN), multi-sensor fusion	• No direct optical response in the visible spectrum • Retrieval relies on correlated variables (temperature, turbidity) • Performance declines in freshwater–brackish transition zones • Strongly site-dependent	• Multispectral reflectance + thermal data • *In-situ* salinity/conductivity measurements • Multi-sensor fusion (optical + thermal/microwave) • Regional calibration datasets

3.3.1 Optically Active Parameters

The determination of Chl-a through satellite RS has been an active area of research due to its ecological negative impact when there are high concentrations during bloom events [16]. Latest research shows significant development in satellite-based Chl-a(Chl-a) retrieval across diverse aquatic systems through physics-based, semi-empirical, and machine-learning approaches. For example, Di Francesco et al. [8] applied semi-empirical spectral indices to improve Chl-a interpolation in small lakes, while Kowe et al. [108] revealed spatial eutrophication patterns via Sentinel-2. Similarly, Salem et al. [72] showed an enhanced Chl-a retrieval performance across low to high concentration conditions. Moreover, hybrid modeling strategies have shown favorable adaptability: Kandasamy et al. [109] integrated deep learning with the QAA algorithm to improve Chl-a prediction across river systems, whereas Tavares et al. [110] found that WaterDetect combined with improved AC produced consistent Chl-a estimates in small lakes. Physics-based QAA/GSM algorithms remained successful in optically complex waters, as demonstrated by Choto et al. [70] in eutrophic systems. Ensemble learning approaches are also gaining attraction; for example, Assaf et al. [111] found that Random Forest outperformed previous machine-learning models for Chl-a prediction in dams by detecting nonlinear spectral interactions. DNN also displayed outstanding results, with Najafzadeh and Basirian [51] reporting high retrieval accuracy for both Chl-a and SDD. Linear models remain useful for seasonal and thermal dynamics, as Dong et al. [98] demonstrated, capturing seasonal Chl-a variability using regression models. In coastal systems, Chen et al. [112] successfully used support vector regression to retrieve Chl-a along with dissolved oxygen and chemical oxygen demand. Jointly, these studies show the growing potential of machine-learning, semi-analytical/absorption-based, and atmospheric-correction-enhanced models for Chl-a retrieval, supporting improved monitoring of trophic status, spatial heterogeneity, and temporal variability across inland and coastal waters.

Several recent studies applied RS and modeling approaches for estimating SDD in inland and coastal waters. Rivera-Ruiz et al. [65] reported that the C2XC algorithm produced the most accurate SDD predictions in eutrophic lakes, specifically under high trophic conditions. Schmidt et al. [64] combined SDD and Chl-a retrievals and revealed that it can support water-quality assessments. Joshi et al. [94] found that RF models successfully predicted SDD for bloom-monitoring applications, while Najafzadeh and Basirian [51] showed that DNN improved SDD prediction accuracy using Sentinel-2 reflectance inputs. In optically complex waters, Qing et al. [66] indicated that improvements to the QAA algorithm enhanced SDD inversion performance. To sum up, these results indicate that both physics-based and machine-learning algorithms continue to advance the retrieval of SDD across diverse water conditions.

One of the most crucial factors in evaluating the quality of water is turbidity, which is also a reliable predictor of the overall number of suspended sediments. RS technologies have the potential to offer an affordable substitute for experimental methods that need a lot of time for field data collection and laboratory analysis in order to evaluate water turbidity over vast areas [37]. The improved prediction performance was observed across diverse water conditions as advances in turbidity retrieval have increased using the combination of satellite-derived reflectance and ML methods. For example, supporting reservoir monitoring applications, Assegide et al. [50] revealed reliable turbidity estimation from Sentinel-2 regression models, while Eljaiek-Urzola et al. [53] developed an empirical model for turbidity estimation using Sentinel-2 images and confirmed a robust retrieval performance using simple band-based reflectance. Ahmad et al. [49] reported that polynomial regression explained 87% of the variance in turbidity derived from Landsat reflectance, indicating strong predictive potential of nonlinear spectral relationships. Steinbach et al. [113] employed RF and GB, showing that turbidity predictions were strongly affected by climate–land cover interactions. In coastal environments, Kong et al. [114] found that RF achieved the highest turbidity retrieval accuracy among the tested ML models, highlighting its suitability for complex marine conditions. The continued integration of empirical regression and machine learning–based retrieval models, particularly those leveraging Sentinel and Landsat imagery, shows a continuing advancement in turbidity monitoring across a wide range of aquatic systems.

Recent advances in total suspended matter (TSM) and suspended particulate matter (SPM) retrieval illustrate a growing shift toward machine-learning and data fusion approaches. Zhang et al. [83] demonstrated that the ESTARFM–PLS framework improved spatiotemporal resolution of SPM predictions by effectively combining multi-source satellite imagery. Using Himawari-8 observations, Patricio-Valerio et al. [115] showed that artificial neural networks generated accurate TSS retrievals, highlighting the capability of geostationary platforms to support high-frequency monitoring. Similarly, Maniyar et al. [116] reported that DNN best predicted TSS concentrations (R^2 = 0.89), outperforming RF and XGBoost, suggesting that deeper architectures may better capture nonlinear reflectance–TSS relationships. In nearshore environments, Igoe et al. [85] demonstrated that XGBoost could estimate suspended sediment concentrations while resolving spatial–temporal variability, showing the ability for dynamic coastal systems. Further, Chen et al. [117] found that DFE-ML improved TSM retrieval by learning nonlinear spectral representations, reinforcing the value of advanced ML feature extraction for sediment-laden waters. These results indicate that deep learning, ensemble ML, and data fusion strategies are advancing SPM/TSS retrieval accuracy and spatial–temporal continuity for coastal and inland water quality monitoring.

The reviewed studies also expanded the application of RS for monitoring thermal-related water quality indicators and their ecological effects. For instance, Ahmed et al. [48] reported that Landsat-derived surface temperature supported low-cost thermal monitoring and facilitated WQI calculation, determined the value of freely available multispectral sensors. Also, Adilakshmi & Venkatesan [47] showed that LASSO regression provided high-accuracy retrieval of water temperature, suggesting that feature selection enhances thermal signal extraction from spectral bands. ML approaches have also advanced thermal anomaly detection, as Luo et al. [82] showed that ML-based models supported real-time lake surface water temperature (LSWT) monitoring, critical for rapid response to heat-stress events. Further highlighting climate–water quality linkages, Kim et al. [75] observed dissolved oxygen decline associated with sea-surface temperature warming retrieved from MODIS/VIIRS imagery. Overall, these studies emphasize that the combination of multispectral satellite data, advanced regression, and ML models provides reliable tools for retrieving water temperature and detecting ecosystem responses tied to thermal variability.

Among other WQPs, CDOM was also observed, for example, Pelevin et al. [89] retrieved CDOM using LIDAR + Sentinel-2 + OC models for lake water, Zhang et al. [118] captured CDOM optical variability and source using MODIS models, and Choto et al. [70] retrieved CDOM with strong accuracy in eutrophic lake waters using absorption-based IOP algorithms.

Salinity retrieval using RS and machine-learning approaches has also been examined. Bygate and Ahmed [87] reported that salinity could be successfully retrieved using ML techniques, with deep neural networks achieving the highest performance following calibration. This result suggests that nonlinear learning models may better capture the indirect spectral relationships associated with salinity variability, particularly when supported by appropriate calibration datasets.

3.3.2 Optically Inactive Parameters

Recent developments in dissolved oxygen (DO) retrieval demonstrate the growing capability of satellite data and machine learning to support aquatic ecosystem assessments. Cao et al. [46] showed that Sentinel-2 regression models enabled accurate DO concentration inversion, highlighting the utility of freely available multispectral imagery. Similarly, modeled DO from Landsat reflectance to support Water Quality Index estimation, emphasizing RS as a cost-effective alternative to *in situ* sensing networks. Dong et al. [119] reported that ML-based DO retrieval captured significant interannual variability, demonstrating sensitivity to long-term environmental signals. In marine waters, Chen et al. [112] demonstrated that support vector regression successfully modeled nonlinear DO responses, reinforcing the advantage of non-parametric models in dynamic oceanic settings. Additionally, Kim et al. [75] monitored DO decline using sea surface temperature–linked satellite proxies, underscoring the importance of RS for detecting climate-induced deoxygenation trends. These advancements suggest that DO retrieval is no longer limited by sensor constraints and by synthesizing the satellite reflectance with thermal proxies, ML-based retrievals provide increasingly reliable DO estimation essential for regional to global water-quality monitoring.

Moreover, recent work has explored the probability of estimating biochemical oxygen demand (BOD/BOD_5) from satellite data and machine-learning techniques. Dawn et al. [79] reported that ML-based models retrieved BOD with a very high accuracy of R^2 = 0.99, which indicates an effective predictive ability. However, it should be interpreted with caution. In this result, the model with the highest accuracy includes all the spectral and water quality indices, land cover data, and meteorological data (precipitation, temperature, and wind speed). Compared to the scenarios using RS indices only and RS indices plus meteorological data, these two scenarios show lower accuracy results. It can be interpreted that sample sizes strongly influenced the accuracy of the report. An independent validation across both space and time is also required for a robust spatiotemporal evaluation, for example, on the variation in the number of *in situ* observations that may influence the model's ability to generalize across different water bodies.

Similarly, Fu et al. [120] found that BOD_5 retrieval performance exceeded other optically active parameters when using ML approaches, suggesting that nonlinear models can capture indirect spectral relationships to biochemical demand. Also, Arias-Rodriquez et al. [121] presented that ML relatively predicted BOD in coastal surface waters, pointing to potential applications for large-area monitoring while also reflecting remaining uncertainty in optically complex settings. While the ML-based retrieval may provide a transferable framework for BOD estimation, the transferability of these models remains contingent on the environment, such as variation with optical complexity and water type.

Chemical Oxygen Demand (COD) retrieval using RS and machine-learning approaches has received increasing attention. For example, Dong et al. [119] reported that CDOM-linked spectral modeling enabled COD retrieval in remote catchments, illustrating the potential of indirect optical proxies when direct absorption features are weak. This implies that the success of COD monitoring often depends on the model's ability to accurately present the body's organic composition. The trend toward using these indirect proxies has been further strengthened by using multi-parameter frameworks. For instance, Cao et al. [46] showed that CODMn could be estimated from Sentinel-2 reflectance with comparatively strong predictive performance. However, the complexity of aquatic conditions often requires more than a single-variable focus. To address this complexity, in a marine context, Chen et al. [112] demonstrated that support vector regression retrieved COD jointly with dissolved oxygen and phosphate, indicating that multi-parameter estimation frameworks may help capture linked biogeochemical interactions. While COD retrieval is feasible using multispectral reflective and ML approaches, the primary constraints remain on the performance stability of proxy selection and water optical conditions.

RS-based total TP retrieval from recent studies highlights the progressively improved capability of ensemble and hybrid machine-learning models. For instance, Sun et al. [58] demonstrated that bagging ensemble approaches reduced TP inversion bias and improved prediction accuracy, highlighting the aid of variance reduction through bootstrap aggregation. Similarly, Zhang et al. [67] applied XGBoost to predict TP dynamics and successfully detected long-term decline trends, illustrating the utility of boosted learners for capturing subtle nutrient trajectories. Taking advantage of Sentinel-2 reflectance, Dong et al. [119] confirmed that machine-learning models efficiently characterized strong seasonal and annual TP variations. Hybrid model integration also proved to be beneficial; for example, Hu et al. [122] reported that GA-ML fusion enhanced TP inversion across multisensor imagery by optimizing feature selection and model parameters, Zhou et al. [57] demonstrated that optimized XGBoost achieved the highest TP retrieval accuracy among tested models, reinforcing its capability for nutrient concentration prediction. Overall, these studies signify that ensemble learning, genetic algorithm–based optimization, and multisensory data fusion are driving developments in TP retrieval reliability, temporal trend detection, and spatial transferability for inland water quality monitoring.

The RS–based retrieval of nitrogen nutrients has evolved in aquatic systems using multispectral imagery and machine-learning approaches. For example, Rodríguez-López et al. [55] retrieved TN in lakes using spectral index regression, showing that reflectance-derived proxies can capture nutrient variability. Another work by Keith [123] demonstrated the feasibility of TN retrieval using Landsat-3 MSS, jointly estimating TN and Chl-a from multispectral reflectance. However, modern approaches have significantly enhanced this accuracy, such as the work of Hu et al. [122], which advanced the TN modeling by integrating genetic algorithms with RF, achieving high prediction accuracy from multi-sensor imagery, including GF-1, Landsat-8, and Sentinel-2, highlighting the benefits of feature optimization and cross-platform integration. This methodological shift establishes that feature optimization is now essential for capturing nutrient variability across diverse aquatic systems.

More recently, Arias-Rodriguez et al. [121] reported moderate prediction performance of machine-learning models for nitrate-N (NO_3-N), albeit with lower accuracy compared to SDD, turbidity, and BOD retrievals, pointing to the challenge of detecting nutrients with weak optical signatures. To overcome this local performance gap, recent efforts have shifted toward global applications, Zhong et al. [78] developed a global nitrate estimation model validated across multi-sensor sea-surface reflectance datasets, demonstrating improved model transferability across regions and oceanographic conditions. The implication is that it indicates that nitrogen retrieval remains challenging but feasible when leveraging spectral indices, optimized ML, and multisensory fusion, with emerging efforts enhancing spatial scalability and prediction reliability for monitoring nutrient enrichment.

Across both optically active and proxy-inferred parameters, retrieval performance is strongly conditioned by AC quality, adjacency effects from surrounding land, and shallow-water bottom reflectance, particularly in narrow rivers, reservoirs, and coastal zones. These factors introduce systematic bias and reduce model transferability if not explicitly addressed. While machine-learning approaches can partially compensate for spectral limitations, their generalization remains constrained by training data representativeness and validation design. Consequently, robust RS-based water quality monitoring requires careful parameter classification, uncertainty reporting, and independent spatial–temporal validation, especially when inferring optically inactive constituents.

3.3.3 Key Gaps and Priorities

Key gaps

- Over-reliance on empirical correlations for optically inactive parameters (e.g., DO, TN/TP, BOD/COD), with limited mechanistic justification and constrained transferability across regions and seasons.
- Insufficient treatment of confounding factors, including atmospheric correction uncertainty, adjacency effects, shallow-water bottom reflectance, and proxy co-linearity among Chl-a, turbidity, and temperature.
- Inadequate validation design, with frequent use of random cross-validation and small sample sizes that risk over-optimistic performance estimates.
- Limited reporting and propagation of uncertainty, particularly when RS-derived parameters are aggregated, interpolated, or combined into indices.
- Scale mismatch between RS products and application needs, especially in narrow rivers, small reservoirs, and fragmented inland waters.

Research priorities

- Explicit separation of robust retrieval and proxy-based estimation, with clear labeling of empirical models as context-dependent unless independently validated.
- Improved validation strategies, emphasizing spatial–temporal independence, multi-site testing, and uncertainty quantification.
- Integration of physically informed and hybrid physics–ML approaches to improve robustness and interpretability of retrievals.
- Multi-sensor and multi-resolution data fusion, combining satellites, UAVs, and *in-situ* measurements to address scale and coverage limitations.
- Uncertainty-aware RS–GIS workflows, ensuring that uncertainty and resolution constraints are transparently communicated in decision-support applications.

Evidence of reporting bias due to missing results was observed across the reviewed studies, particularly in cases where model performance was reported without enough detail on validation strategies, dataset limitations, or unsuccessful model outcomes. Many studies emphasized high prediction accuracy but offered limited information on model uncertainty, negative results, or comparison with alternative methods. This reporting may introduce systematic overestimation of model performance and limit the robustness of synthesized conclusions.

3.4 Retrieval Methods

Across all the reviewed studies, retrieval methods span a continuum from simple empirical band ratios to advanced deep-learning, data fusion, and time-series frameworks. Table 3 shows the summary of the retrieval approaches and observation platforms used in this review.

Table 3: Summary and classification of retrieval approaches and observation platforms used in remote sensing–based surface water quality monitoring reported in the reviewed literature.

Retrieval Methods	Strengths	Limitations	No. of Review Studies
Empirical Regression - Simple/multiple linear and polynomial regression - Band-ratio/index-based empirical models - LASSO regression	• Simple and computationally efficient • High interpretability • Effective with limited datasets • Suitable for rapid, site-specific applications	• Strongly site- and sensor-dependent • Limited transferability • Sensitive to atmospheric correction and optical complexity	28
Analytical and Semi-Analytical Model - Quasi-Analytical Algorithms (QAA) - Coastal/ocean-color algorithms - Hybrid reflectance models	• Physically grounded • Better cross-site interpretability • More robust than pure empirical models for optically active parameters	• Require careful parameterization • Performance degrades in optically complex or shallow waters • Less effective for optically inactive parameters	19
Tree-Based Machine Learning - Random Forest (RF) - Gradient Boosting (GB) - Extreme Gradient Boosting (XGBoost) - CatBoost	• Captures nonlinear relationships • High predictive accuracy • Handles multi-parameter retrieval well • Relatively robust to noise	• Data-intensive • Limited physical interpretability • Risk of overfitting without independent spatial–temporal validation	42
Kernel-based Machine Learning - Support Vector Regression (SVR)	• Effective for small to medium datasets • Strong performance for nonlinear relationships	• Sensitive to kernel choice and parameter tuning • Scaling to large datasets can be computationally expensive	17
Neural Networks and Deep-Learning - Artificial Neural Network (ANN) - Deep Neural Network (DNN) - Convolutional Neural Network (CNN) - Recurrent Neural Network (RNN) - Bayesian probabilistic neural networks (BNNs) - Mixture Density Networks	• Highest accuracy in complex systems • Captures spatial–spectral–temporal patterns • Probabilistic variants allow uncertainty estimation	• Require large, diverse training datasets • Low interpretability • Limited transferability across regions/seasons	26
Hybrid Physics-ML Approaches - QAA-derived featres + ML - GA-XGBoost - Physics-guided ML	• Combines physical consistency with ML flexibility • Improved robustness and generalization	• Increased methodological complexity • Higher data and expertise requirements	11

(Continued)

Table 3 (continued)

Retrieval Methods	Strengths	Limitations	No. of Review Studies
Data Fusion, Data Assimilation - Ensemble Kalman Filter (EnKF) - Optimal Estimation (OE)	• Enhance spatiotemporal resolution • Reduce data gaps • Suitable for long-term monitoring	• Computationally intensive • Requires multi-sensor harmonization and model infrastructure	9
Geostatistical Interpolation and GIS-Integrated Regression - Inverse Distance Weighting (IDW) - Kriging	• Useful for visualization and decision support • Integrates RS with • management tools	• Interpolation propagates sampling error • Strongly dependent on • sampling density	7
Unmanned Platforms - Unmanned Aerial Vehicle (UAV) - Unmanned Surface Vehicle (USV) - Proximal hyperspectral systems	• Ultra-high spatial resolution • Flexible deployment • Ideal for small or narrow water bodies	• Limited spatial extent • Seasonal/site specificity • Not scalable alone for regional monitoring	12

3.4.1 Empirical Band Ratios, Spectral Indices, and Classical Regression

The first large group relies on empirical relationships between reflectance and water quality. These empirical approaches are easy to implement and often perform strongly in site-specific calibrations, but they tend to be region- and sensor-dependent and may struggle with transferability to other water types. These methods are more physically interpretable and often more transferable across sites than purely empirical regressions, but they require careful parameterization of IOPs and often need local tuning. Many studies develop uni- or multivariate regression models from individual bands or band combinations to retrieve turbidity, nutrients, and other WQPs (e.g., one-dimensional regression on NIR bands for DO, TN, TP, and turbidity in Sentinel-2 data) by Cao et al. [46]; OLS and polynomial regression for turbidity from Landsat-8 band combinations by Ahmad et al. [49]; multiple linear regression for DO, Chl-a, TSM, and thermal effluents by Dong et al. [98]; and multiple linear or multivariate regression for nitrate and water color by Zhong et al. [78]. Several works build empirical algorithms using specific band ratios or indices: B5/B4, B4/B3, and single-band models for Chl-a, turbidity, and TSS from Sentinel-2 [50]; NDVI-based empirical models for TN, turbidity, Chl-a, and TSS [108,124]; red-band empirical turbidity and SDD models from Sentinel-2 [53]; multi-band indices such as NDCI, NDAI, MCI, and CI from drone RGB/multispectral imagery [100]. LASSO regression is used to select informative bands/indices and build parsimonious predictive models for multiple parameters (temperature, TDS, pH, turbidity, Chl-a, DO, BGA) from Landsat-8 in rivers [47,48]. Multivariate Adaptive Regression Splines (MARS), Gene Expression Programming (GEP), and Evolutionary Polynomial Regression (EPR) are applied to derive WQI or individual WQPs from Landsat-8 [51].

3.4.2 Semi-Analytical and Analytical Bio-Optical Algorithms

A second family uses physics-informed, semi-analytical, or fully analytical models linking inherent/optical properties to constituent concentrations: (a) The classic QAA (e.g., QAA v5/v6) is used to retrieve Chl-a and other IOPs from satellite reflectance, sometimes coupled to AI: for Chl-a from Landsat/MERIS [109]; for Secchi depth (ZSD) in lakes [66]; and in a suite of IOP algorithms (QAA_v6, GSM, GIOP-DC, PML, LMI) to derive specific absorption terms and then water quality variables such as Chl-a and suspended solids [70]. (b) Ocean-color style algorithms are widely used: OC2 and Nechad algorithms for Chl-a and TSS from Sentinel-2 and *in situ* LIDAR/S2 data [89,92]; the JAXA Chl-a Version-2 algorithm, which merges a color index algorithm for low Chl-a with OCx algorithms for high Chl-a and also derives TSM [72]. (c) ESTARFM-based spatiotemporal fusion is combined with PLS regression to retrieve SPM at improved spatial/temporal resolution [83]. Semi-empirical band-index models are used with ACOLITE-processed PlanetScope and Sentinel-2 to estimate Chl-a, turbidity, and cyanobacteria in lakes [8], or to retrieve Chl-a and DOC/CDOM in lakes [118]. Semi-analytical Chl-a retrieval from multi-sensor ocean color data is used for coastal hazard monitoring [77] and for Sentinel-3 OLCI in lakes [73].

3.4.3 Machine Learning Regression

Additionally, to date, the most widely used RS estimation model is based on cutting-edge ML/AI technology. A large group of studies use supervised machine learning to map spectral features (bands, indices, or IOPs) to WQPs. These methods exploit non-linear relationships in feature space, often outperforming traditional empirical or semi-analytical algorithms, but they are highly sensitive to training data quality and representativeness. RF and GB are used for turbidity prediction from Sentinel-2 plus ancillary data [113]; turbidity and nutrients from Sentinel-2/Landsat [40,82,100]; Chl-a, TN, TP, and multi-parameter lake eutrophication indices [94,95,125,126]; CDOM and DOC [127]; TSM and TSS in coastal/marine waters [60,97]. Gradient boosting trees or boosted regression trees are also used to link long-term Chl-a/turbidity trends to catchment pressures [90]. XGBoost is a dominant retrieval method for Chl-a, TP, TN, turbidity, and LSWT: e.g., turbidity retrieval with MSI/OLI [57]; TN and TP using MODIS-derived reflectance [67]; algal biomass abundance [128]; hybrid GA-XGB models for TP from UAV imagery [43]; TP inversion from Sentinel-2 [56,57]; LSWT forecasting from proximal hyperspectral data [82]; and coastal Chl-a mapping from combined Sentinel-1/2/3 [129]. CatBoost appears both as a stand-alone regressor and within hybrid or ensemble frameworks [109,111,119]. SVR is used for Chl-a and turbidity retrieval from OLCI, HLS, and combined satellite products [127,130]; SVM is applied to retrieve pH, DO, TSS, and TDS from Sentinel-2/ResourceSat-2 [131] and to support algal bloom prediction [96].

3.4.4 Neural Networks and Deep-Learning Frameworks

Beyond classical ML, many studies deploy ANN and deep networks. These deep-learning approaches provide high accuracy and explicit uncertainty estimates (in the Bayesian/MDN cases), but often require large, diverse training datasets, which the studies repeatedly identify as a key limitation. Standard ANN and MLP-based DNNs are used for TDS and TSS from Landsat-8 [97,132], for Chl-a/TSM and CyanoHABs from MERIS/OLCI [71,133], and for multi-parameter lake water quality [52]. CNNs and deep feature extraction–ML fusion frameworks are used to extract spatial–spectral features and then feed SVR/RF regressors for TSM [117], to delineate algal bloom area [134], and to estimate Chl-a from Sentinel-2 MSI in Poyang Lake [135]. Deep Feature Extraction + ML (DFE-ML) and transfer-learning-based networks (e.g., TLNet) further appear in UAV-based urban river monitoring [101]. Time-aware LSTM and RNN architectures are implemented to model temporal Chl-a dynamics from Landsat-8 [55] and for forecasting eutrophication states or LSWT when combined with meteorological forcing. NBeats time-series models are coupled to CatBoost and QAA in [109] for time-series chlorophyll retrieval. Bayesian probabilistic neural networks (BNNs) are used to retrieve Chl-a and quantify uncertainty across OLCI/MSI [136], while Mixture Density Networks (MDNs) are used to retrieve cyanoHAB magnitude and probability from Sentinel-2/3 data [84].

3.4.5 Data Fusion, Data Assimilation, and Optimal Estimation

Several studies treat retrieval as a data assimilation or fusion problem. These methods integrate multi-sensor EO data with process-based models, enabling gap-filling and higher temporal resolution, but they require significant modelling infrastructure and expert knowledge. MERIS Chl-a products are assimilated into a coastal model using Ensemble Kalman filtering and smoothing to generate daily Chl-a fields in the Baltic Sea (MERIS–EnKF). CLMS and ESA CCI lake temperature, turbidity, and Chl-a are retrieved using Optimal Estimation from AATSR, SLSTR, MERIS, and OLCI L1 data [79]. Enhanced spatiotemporal reflectance products are created via ESTARFM [83] or via particle-tracking/numerical hydrodynamic models [137], after which regression/PLS is used to retrieve SPM and TSM.

3.4.6 Retrieval from Unmanned Platforms (UAVs, USVs, Proximal Sensors)

Finally, a group of studies uses proximal sensing platforms with retrieval methods like satellite-based ones. These studies extend retrieval techniques to very high spatial/temporal resolution, but note limitations in spatial coverage, cost, and seasonal representativeness. GA-optimized XGBoost (GA-XGB) for TP from UAV multispectral imagery [43]; TLNet, CNN, LSTM, Transformer, and conventional ML for TN, DO, TSS, and Chl-a in urban rivers [101]; random forest, GBM, XGB, and KNN for *E. coli* from drone RGB imagery [99]. Hyperspectral proximal sensing (HPSs) combined with XGBoost, DNN, and KNN is used to forecast LSWT at hourly scales [82]. USV-mounted sensors produce dense point measurements that are interpolated via IDW/Kriging [44].

3.4.7 Geostatistical Interpolation and GIS-Integrated Regression

A smaller group employs spatial interpolation or GIS–statistical coupling. Although not "spectral inversion" in the strict sense, these interpolation-type methods are retrieval procedures for spatial fields of water-quality indicators. Kriging and inverse distance weighting (IDW) are used to interpolate Chl-a from *in situ* measurements collected by unmanned surface vehicles (USVs), generating spatially continuous Chl-a maps [44]. Stepwise regression combined with RS-derived indices in a GIS environment is used to build predictive models for multiple physico-chemical parameters in lakes [138]. Across the reviewed studies, retrieval approaches have evolved along three main trajectories: (1) from simple empirical regressions to sophisticated ML and deep learning. Early and simpler studies rely on band ratios, indices, and linear/polynomial regression, which remain valuable for transparent, low-data settings. However, most recent work favours tree-based ensembles (RF, XGBoost, CatBoost), ANNs/DNNs, CNNs, and LSTMs because they better capture non-linear and multivariate relationships, especially for complex or non-optically active parameters (TN, TP, DO, BOD, nutrients, *E. coli*). These methods routinely outperform empirical and even some semi-analytical algorithms, but depend heavily on large, well-distributed training sets and careful cross-validation, (2) from purely data-driven to hybrid physics–ML and fusion frameworks. Semi-analytical/bio-optical algorithms (QAA, GSM, Nechad, OCx/CI) and sophisticated AC (ACOLITE, C2RCC, GRS) remain central, particularly where transferability and physical interpretability are priorities. A clear trend is to combine these physically based products with ML (e.g., QAA-derived IOPs used as ML features, ESTARFM + PLS, EnKF, or OE-based data assimilation feeding ML predictors), enabling robust, high-frequency retrievals while preserving physical consistency, and (3) towards spatiotemporal, multi-platform, and uncertainty-aware retrieval. Increasingly, studies treat retrieval as a spatiotemporal forecasting and data-fusion problem: time-series models (ARIMA, NBeats), BRT trend analysis, LSWT and Chl-a forecasting, and multi-sensor fusion across MODIS, OLCI, MSI, OLI, UAVs, USVs, and proximal sensors. Probabilistic deep networks (BNN, MDN) explicitly estimate uncertainty, and data assimilation frameworks address observational gaps. Unmanned platforms and proximal hyperspectral systems push towards real-time, high-frequency monitoring, but their models still face challenges in scaling beyond individual sites or seasons.

Fig. 2 illustrates a hierarchical framework of retrieval methods underpinning RS–based water quality monitoring. The framework demonstrates the progressive evolution of retrieval approaches—from simple empirical regressions to semi-analytical ocean-color algorithms, machine learning and deep learning models, data assimilation/time-series fusion strategies, and emerging unmanned and proximal sensing systems. This hierarchy emphasizes increasing capability, scalability, and uncertainty awareness in retrieving key water quality parameters. By mapping these methodological tiers to their resulting applications in inland and coastal monitoring, early-warning systems, and policy decision support, the figure highlights how advances in retrieval science contribute to more accurate, continuous, and operational water quality assessment.

3.5 GIS Integration in Water Quality Monitoring

A Geographic Information System (GIS) is an important aspect of environmental monitoring because it combines geospatial data and environmental data to conduct spatial analyses as well as gain a visual aspect [139]. GIS can help identify water quality, locate discharge sites for industrial wastewater, examine the dispersion of pollutants, and help designate areas of concern [140]. GIS can assist in facilitating pollution risk mapping, assist in hydrological modeling, and support assessments of pollution in transportation dimensions in river ecosystems [141].

3.5.1 Conceptual RS–GIS Integration Framework

Geographic information systems provide techniques for storing, processing, and controlling a large amount of information derived from Remote Sensing Devices [138]. In the reviewed literature, GIS functions as a critical integrative layer that links remotely sensed (RS) water quality products with spatial context, ancillary datasets, and decision-support workflows. A generalized RS–GIS integration framework can be conceptualized as a three-stage process: (i) RS-derived parameter retrieval, where water quality parameters (e.g., chlorophyll-a, turbidity, total suspended solids, nutrients) are retrieved from satellite or UAV imagery using empirical, semi-analytical, or machine-learning approaches [15,106]; (ii) GIS-based spatial analysis and inference, and (iii) management-oriented interpretation. These spatially continuous RS products are subsequently imported into GIS environments, where they are combined with hydrological networks, land-use data, administrative boundaries, and *in-situ* observations to enable spatial inference and visualization [16].

This framework highlights that GIS does not independently generate water quality information, but rather facilitates interpretation, scaling, and decision relevance of RS-derived estimates. Consequently, the reliability of RS–GIS integration depends strongly on how spatial resolution, uncertainty, and hydrological structure are treated across these stages.

3.5.2 Typical GIS-Enabled Inference Modes

GIS provides several recurring inference modes within the reviewed studies. The most widely used approach is spatial interpolation and surface modeling, where point-based *in-situ* measurements or RS-derived retrievals are interpolated using methods such as inverse distance weighting (IDW) or kriging to infer continuous water quality maps. While effective for visualization, these approaches assume spatial stationarity relationships, which may not reflect hydrologically driven transport processes.

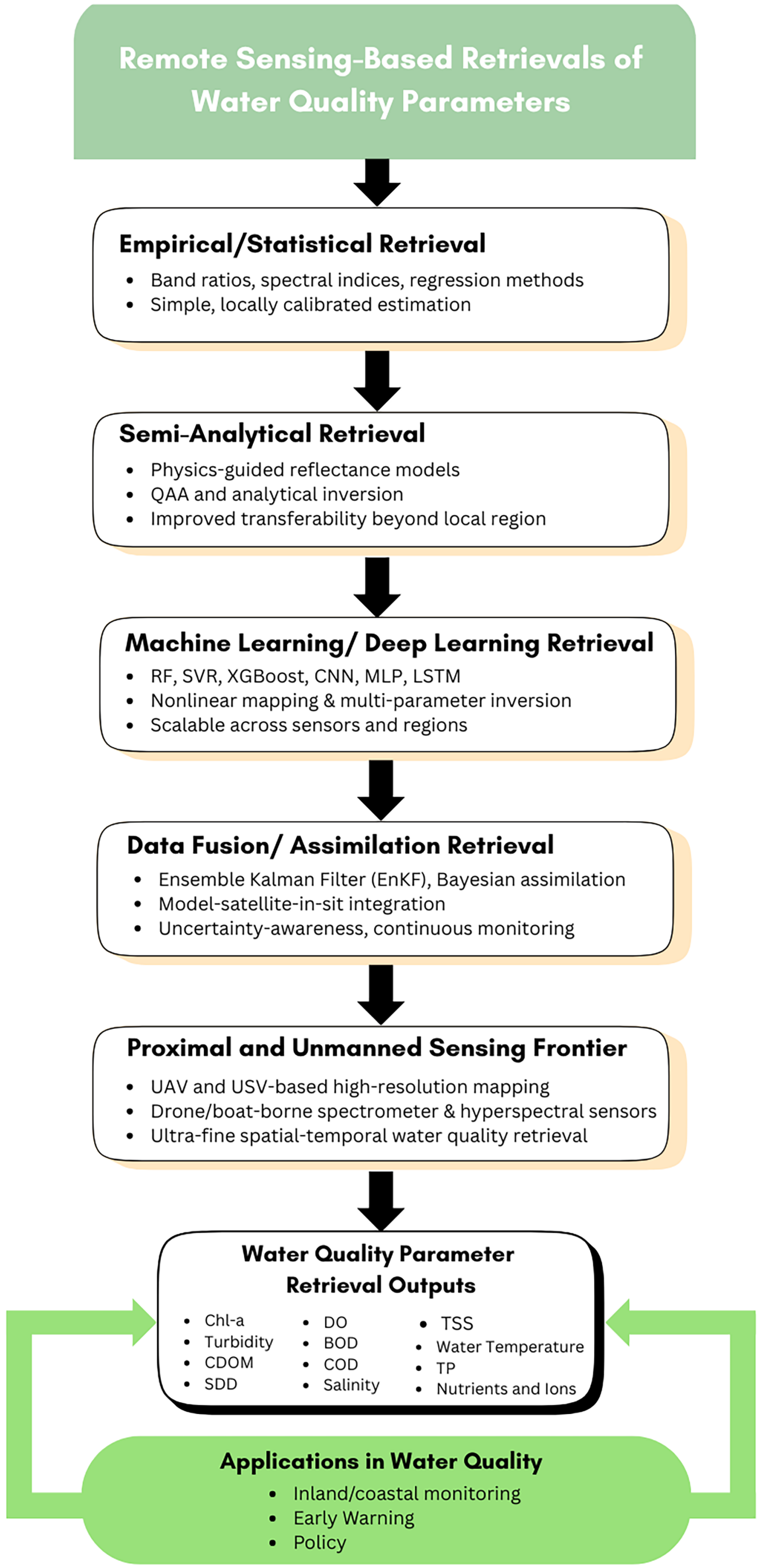

Figure 2: Hierarchical framework of RS retrieval methods and their applications in surface water quality monitoring.

A second inference mode involves zonal statistics and overlays analysis, where RS-derived water quality parameters are aggregated within hydrological units, administrative boundaries, irrigation command areas, or reservoir extents [8,48]. This approach is commonly applied in water quality compliance monitoring and reporting but may mask sub-pixel variability and localized pollution gradients when medium-resolution RS products are aggregated to fine management units.

Another mode is index-based synthesis, particularly through GIS-implemented Water Quality Index (WQI) mapping. WQI integrates multiple parameters into a single score to support communication and decision-making [26]. However, several studies note that GIS-based WQI maps can obscure parameter-specific exceedances, amplify uncertainty when RS-derived proxies are used, and create an illusion of spatial precision that exceeds the robustness of the underlying inputs [27].

More recent work combines machine-learning–assisted GIS inference, where RS products, terrain attributes, land use, and hydrological variables are jointly analyzed within GIS environments to identify pollution drivers, hotspots, or vulnerability zones [54]. Despite its potential, these approaches are sensitive to training data representativeness and spatial autocorrelation.

3.5.3 Scale, Uncertainty, and Connectivity Considerations

A central limitation identified across the literature is scale mismatch between RS products and GIS layers. Medium-resolution satellite data (10–30 m) are frequently integrated with fine-scale GIS features such as narrow river networks, point-source locations, or irrigation canals, leading to spatial averaging effects and misrepresentation of localized water quality gradients [142]. This issue is particularly pronounced in narrow rivers, small reservoirs, and fragmented inland waters, where mixed land–water pixels and adjacency effects further degrade retrieval accuracy [103,143].

Uncertainty propagation is another persistent challenge. Many GIS-based studies visualize RS-derived products without explicitly communicating retrieval uncertainty, validation limits, or sensitivity to atmospheric correction and proxy co-linearity. When these products are subsequently interpolated, aggregated, or combined into indices such as WQI, uncertainty can compound and become difficult to trace.

Finally, hydrological connectivity is often inadequately represented in GIS analyses. Interpolation and overlay methods commonly neglect flow direction, upstream–downstream relationships, residence time, and mixing processes that govern water quality dynamics in river networks and irrigation systems [16]. As a result, spatial proximity in GIS does not necessarily correspond to hydrological influence, limiting the interpretability of mapped patterns.

3.5.4 Implications for Operational RS–GIS Integration

Moving beyond simple data layering, the reviewed evidence indicates that GIS integration in water quality monitoring should be treated as a decision-support and interpretation layer, rather than a purely analytical extension of RS retrieval. Robust RS–GIS integration requires explicit alignment between sensor resolution and GIS analysis scale, careful selection of inference modes, and transparent reporting of uncertainty and validation constraints. Emerging approaches that combine multi-resolution RS data, hydrologically informed GIS analysis, and uncertainty-aware visualization show promise but remain underdeveloped in operational practice.

Table 4 shows the summary of the synthesized and reviewed literature according to study objectives, which highlights how recent studies contribute to addressing limitations of traditional monitoring and advancing scalable RS–GIS-based water quality assessment frameworks.

Table 4: Summary of reviewed studies aligned with study objectives.

Study Objective	Key General Findings	Implication for the Research Problem
1. Evaluate the RS capability for water quality monitoring	RS effectively retrieves optically active parameters across large spatial scales	Supports transition from point sampling to basin-scale monitoring
2. Assess ML-based retrieval performance	ML improves the prediction of optically inactive parameters using proxy relationships	Enables monitoring of parameters lacking a direct spectral response
3. Investigate multi-sensor integration	Multi-platform integration improves temporal coverage and reduces uncertainty	Supports operational and near-real-time monitoring frameworks
4. Evaluate RS–GIS decision support capability	GIS enhances spatial interpretation and watershed-scale analysis	Improves environmental management and policy planning
5. Identify technological and methodological gaps	Challenges remain in calibration, atmospheric correction, and transferability	Highlights the need for hybrid models and standardized workflows

4 Discussion

4.1 Interpretation of Results in Relation to Existing Literature

The synthesis indicates that RS-based surface water quality monitoring has progressed from a supplementary role to become a central spatial framework for environmental evaluation. Rather than a replacement for field sampling, RS addresses the limitation of localized observations by enabling spatially continuous and repeatable monitoring. This reflects a broader methodological shift in literature from point-based measurement toward system-scale environmental assessment.

The reviewed evidence demonstrated that a critical distinction emerged from concerns about optically active and optically inactive parameters. The foundational strength of the retrieval of optically active parameters is comparatively robust and reinforced by semi-analytical and empirical models with demonstrated regional applicability [106], while estimation of optically inactive parameters increasingly relies on machine-learning (ML) models that exploit indirect spectral proxies and nonlinear relationships. Although ML models often outperform traditional approaches in estimating optically inactive parameters, this performance reflects improved proxy modeling rather than true optical retrieval. As such, ML expands the inferential capacity of RS but does not eliminate the structural constraints associated with calibration dependency, transferability, and validation.

The transition from the reliability of single sensors moving towards the multi-sensor and multi-platform integration using satellite, UAV, thermal, radar, and *in-situ* observations also shows as a consistent pattern in RS water quality monitoring. This integration mitigates resolution trade-offs, reduces cloud-related gaps, and enhances temporal continuity [97,144]. This shows that RS-based monitoring is turning into an integrated observing system rather than a single-algorithm solution. By taking advantage of its complementary strengths across platforms, it may solve the data limitations and improve observational continuity.

The role of GIS further highlights this transition. When RS-derived parameters are integrated within geospatial workflows, such as hotspot mapping, watershed-scale interpolation, and scenario analysis, they shift from descriptive indicators to decision-support tools. This integration connects spectral retrieval, enabling spatially explicit environmental management. However, there are still determined constraints, such as atmospheric correction uncertainty, adjacency effects, shallow-water interference, and limited spatial–temporal validation, that continue to restrict model generalizability [102]. These factors may introduce systematic preference and increase sensitivity to local optical conditions, which reduces the robustness of retrieval algorithms across different water bodies.

Generally, the reviewed literature suggests that the field is transitioning from algorithm optimization toward system-level robustness. Future progress depends not only on improving retrieval accuracy, but on developing transferable, uncertainty-explicit, and scalable RS–GIS monitoring architectures.

4.2 Theoretical and Practical Implications

The findings from this review strengthen the theoretical framework of surface water quality monitoring by explicitly distinguishing the conceptual boundary between optically active and optically inactive water quality parameters. It is evident that while optically active parameters are governed by direct bio-optical interactions, optically inactive parameters are fundamentally proxy-based and dependent on indirect light-based measurement. The distinctions between these parameters have important theoretical implications as it highlights the retrieval uncertainty and transferability, which means that RS-based water quality monitoring is parameter-dependent rather than sensor- or algorithm-dependent. The results further contribute to the growing RS-based theoretical framework by emphasizing the role of ML as an extension to water quality monitoring, which supports the emerging hybrid paradigm of combining physical features and data-driven approaches to enhance robustness, generalization, and interpretability in water quality retrievals. In terms of sensors and platforms, the findings from the reviewed literature indicate that no single sensor can resolve all spatial, temporal, and spectral requirements of water quality monitoring. These results synthesize the evidence supporting that integrated observation systems, by combining satellite RS, UAVs, *in-situ* sensors, and GIS, represent a fundamental evolution toward scalable and uncertainty-aware monitoring frameworks.

From a practical perspective, the findings support that RS can extensively facilitate a paradigm shift from assessments from discrete point-based sampling to basin- and watershed-scale assessments. This capability is especially important for data-scarce regions with a lack of monitoring infrastructure, in which RS can provide cost-effective, repeatable, and spatially comprehensive information. As ML approaches demonstrates its effectiveness, they also have practical implications when compared to the traditional water quality monitoring, which is known to be time-intensive and expensive. This review highlights that using ML-based water quality monitoring requires careful calibration, validation, and uncertainty reporting. Lastly, the RS-GIS integration provides a robust framework for environmental governance and policy formulation through spatial visualization, hotspot identification, trend analysis, and scenario evaluation. This workflow can substantially support evidence-based decision-making in watershed management, pollution control, and land-use planning.

4.3 Gaps, Inconsistencies, and Future Research Directions

This review highlights significant progress in the application of RS and GIS for surface water quality monitoring; however, a synthesis of the literature reveals several gaps, inconsistencies, and challenges that limit operational deployment and scientific generalization. This review is also subject to several methodological limitations. The literature search was limited to the selected databases and types of publications, which may not capture other relevant data from other sources. Additionally, a qualitative synthesis was performed due to the significant heterogeneity in study designs, sensors, and analytical approaches, which precluded quantitative meta-analysis.

Despite the advancements highlighted in this review, the available evidence presents several limitations that affect the overall confidence in the findings. Several studies rely on empirical and machine learning–based models that are calibrated using limited or site-specific datasets, which may limit their transferability across different regions and varying environmental conditions. The extensive use of indirect proxy relationships for optically inactive parameters further introduces uncertainty due to weak spectral signals.

Behind these limitations, future research directions have been recommended for a robust decision-support tool in water quality monitoring.

4.3.1 RS Retrieval Gaps and Inconsistencies

Despite significant advancements in RS applications for water quality monitoring, the reviewed studies show various technical and methodological challenges and limitations that affect retrieval accuracy, spatial–temporal representativeness, and operational transferability. Various sensors are limited by insufficient resolution to capture localized-scale spatial heterogeneity in rivers, small lakes, or fragmented water bodies. For example, the 30 m resolution of Landsat imagery was insufficient for narrow inlets and complex lake fringes in BOD and TSS retrieval [79], while low sample density in river networks constrained accurate pollution mapping [145]. Similarly, limited revisit frequency in Sentinel-2 imagery resulted in temporal gaps that prevented continuous intra-seasonal monitoring [137]. Numerous optical RS studies emphasize signal degradation caused by atmospheric aerosols, adjacency effects from surrounding land, water-surface sun glint, and cloud-induced pixel contamination. For instance, adjacency effects have been shown to alter near-infrared (NIR) reflectance, thereby reducing the accuracy of lake water quality retrievals [110], while inconsistent pixels from cloud and ship shadows affected turbidity and TN/TP uncertainty [56]. These studies highlight the ongoing need for improved AC algorithms tailored to inland and coastal waters.

An extensive constraint is the insufficient number, coverage, and spatiotemporal alignment of ground measurements for model training, calibration, and validation. Work on coastal turbidity by [138] noted limited *in-situ* matchups for validating C2RCC retrievals. Similarly, sparse high-concentration nutrient samples reduced high-end predictive accuracy in TP/TN studies using XGBoost [67]. These constraints hinder model generalizability and confidence in extreme-value pollution assessment. Many retrieval models perform well only for a single region, season, water type, or algorithm–sensor pairing. For example, semi-empirical procedures for PlanetScope could not be directly transferred to other reservoirs [8], and algorithm performance varied with trophic state levels for Secchi depth retrievals [65]. This exposes the need for region-independent and multiscale transferable retrieval frameworks.

Several parameters (e.g., nutrients, metals, COD, salinity) exhibit weak spectral signatures, leading to higher uncertainties relative to optically active variables such as Chl-a or turbidity. The COCTS SPM products suffered algorithm limitations compared to Chl-a estimates, necessitating algorithm refinement. Similarly, Landsat sensor band limitations restricted Chl-a retrieval accuracy due to the absence of red-edge bands [146].

4.3.2 GIS Integration Gaps and Inconsistencies

While GIS techniques enhance spatial analysis, visualization, and decision support, the reviewed studies identify several limitations related to data sparsity, temporal coverage, and workflow consistency.

Several reviewed studies integrate medium-resolution satellite–derived water quality products (e.g., Landsat-8 OLI, Sentinel-2 MSI) with fine-scale GIS layers such as river networks, point-source locations, administrative boundaries, and management units. While this integration enhances spatial visualization and decision support, a recurring limitation identified in the literature is scale mismatch between satellite pixel resolution and the spatial granularity of GIS features. Medium-resolution pixels often spatially average reflectance signals over heterogeneous surfaces, which can obscure localized pollution gradients and introduce uncertainty when mapped onto narrow rivers, small reservoirs, or fragmented water bodies [15,106]. Also, the reviewed studies demonstrate that narrow river channels and small inland waters are frequently under-resolved by medium-resolution imagery, leading to mixed land–water pixels and biased water quality estimates when integrated into GIS frameworks [8,147]. This issue becomes particularly pronounced when GIS layers representing point sources or hydrological features are interpreted at scales finer than the effective resolution of the RS product, resulting in apparent spatial precision that exceeds the underlying data support.

The literature further indicates that scale mismatch interacts with adjacency effects and pixel contamination, especially in riverine and nearshore environments, compounding uncertainty in RS–GIS outputs [103,143]. Studies relying on GIS-based interpolation or zonal statistics without accounting for sensor resolution or mixed-pixel effects risk propagating these uncertainties into downstream analyses, including watershed prioritization and regulatory assessment.

Recent work highlights that higher-resolution commercial satellites, UAVs, or multi-sensor data fusion can partially mitigate scale mismatch, but these approaches remain limited by cost, coverage, and operational constraints [8,80]. Consequently, the reviewed evidence suggests that GIS integration should be accompanied by explicit discussion of scale compatibility and uncertainty, rather than treating satellite-derived products as directly comparable to fine-scale spatial layers.

GIS-based inverse distance weighting (IDW), kriging, or trend interpolation propagates error in data-scarce river basins. Several GIS-based suitability and WQI mapping studies highlight uncertainty linked to short monitoring periods [148] and sparse sampling networks lacking hydrochemical diversity [149]. The inability to capture long-term hydro-climatic variability weakens inference regarding seasonal or climate-driven processes. Combined RS + GIS workflows frequently suffer from inconsistent radiometry and AC between sensors, temporal mismatch, insufficient metadata, or a lack of harmonization workflows. Inter-sensor mismatch between MERIS/Sentinel-3 MSI/OLCI datasets undermined continuous Chl-a records and uncertainty quantification [136].

Overall, this critical review indicates that scale mismatch remains a fundamental limitation in RS–GIS-based water quality studies. Addressing this challenge requires careful alignment between sensor resolution and GIS analysis scale, transparent reporting of spatial uncertainty, and cautious interpretation of fine-scale patterns derived from medium-resolution satellite data.

4.3.3 Future Research Directions

A structured roadmap (Fig. 3) that outlines strategic priorities for advancing RS–GIS integration in surface water quality monitoring was developed from the technical challenges and emerging innovations identified across the literature. The roadmap positions the current limitations and aligned future directions across four interconnected pillars: (1) improving sensor, retrieval, and preprocessing foundations; (2) integrating multisource RS products; (3) standardized RS–GIS workflows for real-time, scalable deployment; and (4) embedding scientific outputs within governance and decision-support systems.

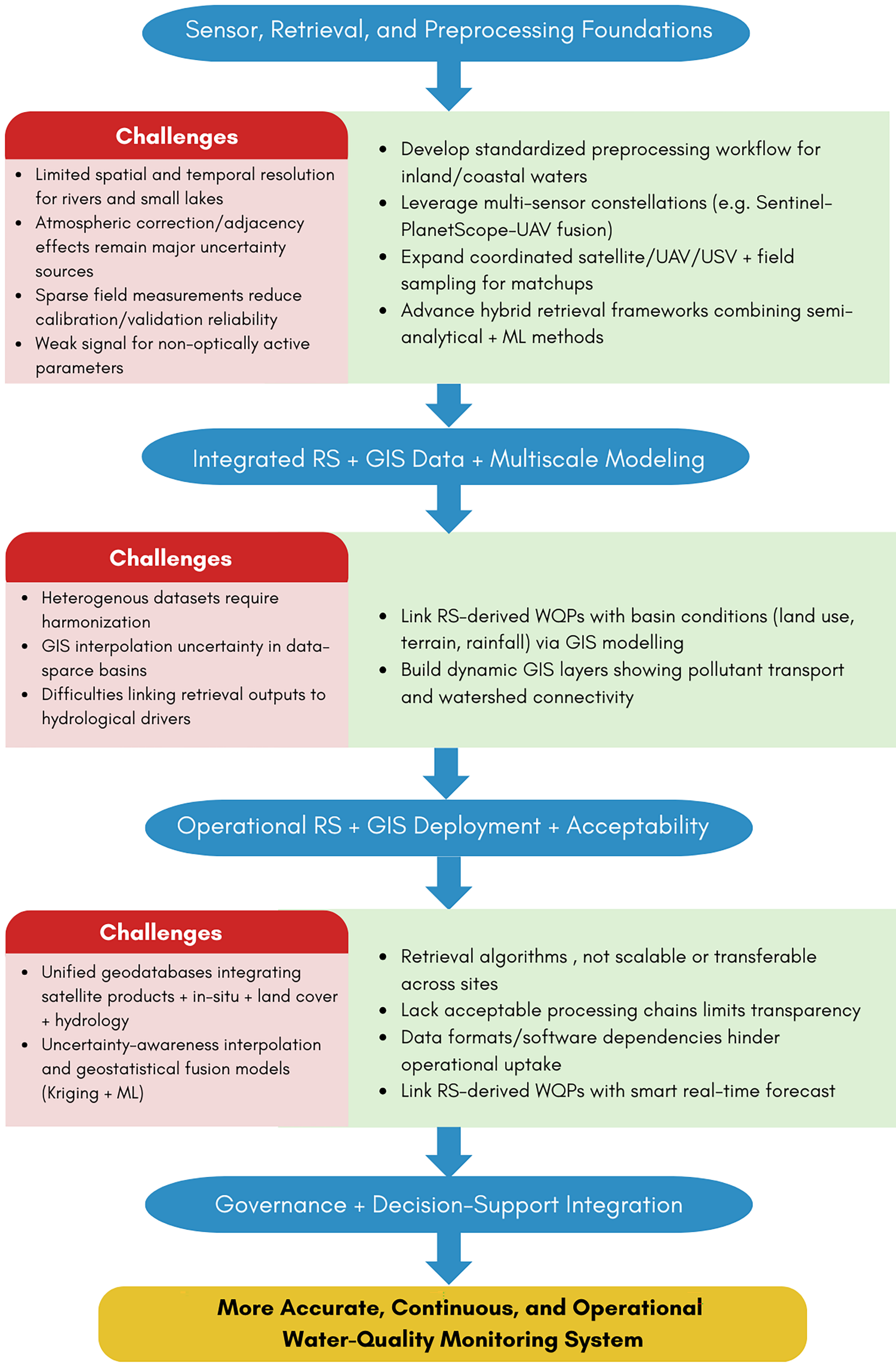

Figure 3: Proposed roadmap for advancing RS–GIS integration in surface water quality monitoring systems.

Pillar 1: Sensors, Retrieval, and Preprocessing Foundations

The consistent challenges in atmospheric correction, uncertainty, limited spatiotemporal resolution, validation, and calibration reliability continue to limit the model transferability. Therefore, robust retrieval and standardized preprocessing are needed to provide reliable water quality monitoring. The future directions also highlight long-term, multi-scale observation approaches. Works on the transferability of hybrid ML retrieval frameworks should integrate physically meaningful inputs (e.g., inherent optical properties, water-type classifications, or semi-analytical outputs) into ML architectures. A hybrid ML that upholds high predictive accuracy while improving interpretability and stability across sites, especially for proxy-inferred parameters, will represent a substantial methodological advance. Higher-quality calibration and prioritizing spatially and temporally independent validation strategies, such as independent regional validation, and not relying on a random data split. To do this, hybrid ML approaches, physics-informed retrieval, and standardized frameworks should prioritize clearly determining uncertainties. By considering these approaches, methodological robustness at this level may avoid model reliability limitations.

Pillar 2: Multi-Source and Multi-Resolution Integration

Many works emphasize the need to extend monitoring beyond short-term case studies by expanding spatial and temporal coverage, for example, GIS- and MCDA-based lake assessments recommend multi-year datasets to capture seasonal variability and ecosystem change [149] and increasing the number of monitoring stations to improve calibration and validation [146]. For example, future modeling suggests the integration of advanced ML techniques and multi-sensor datasets to obtain more scalable eutrophication and turbidity retrieval systems [62].

With the integration of multi-source and resolution, several works highlight the necessity of integrating operational implementation of water quality retrievals within RS-GIS-enabled planning tools and management frameworks for rivers, lakes, and coastal areas. Tighter coupling of RS–GIS analytics with water management decision systems, such as linking the RS-GIS derived results with regulatory standard thresholds and management indicators. By doing this, policy makers and water managers will be guided efficiently for early warning, compliance assessment, and planning.

Pillar 3: Embedding RS-GIS Standardized and Transferable Workflows

Despite strong predictive performance in many studies, reproducibility and generalizability remain limited across diverse environmental conditions. Operational deployment requires standardized preprocessing pipelines, open validation protocols, uncertainty reporting standards, and cross-basin model testing. Standardization transforms individual methodological advances into transferable monitoring systems. This pillar addresses the gap in experimental research and implementation. The ultimate value of RS-derived parameters lies in their integration into a spatial decision-support framework, such as GIS-based hotspot mapping, watershed-scale interpolation, scenario analysis, and policy-aligned indicators that convert spectral retrieval into an evidence-based water quality assessment [148]. Integrating RS outputs within geospatial structures shifts monitoring from descriptive mapping to adaptive water quality monitoring and management.

Pillar 4: Decision-Support

Taken together, these four pillars redefine RS–GIS monitoring as an integrated architecture roadmap to move from foundational spectral reliability to system-level integration, aligning methodological advancement with operational applicability.

5 Conclusion

This review combines advances in the integration of RS and GIS technologies for surface water quality monitoring and demonstrates the paradigm-shifting potential of these tools to overcome the challenges and limitations of traditional approaches to water quality monitoring and assessment, highlighting a clear methodological transition from site-specific, point-based observation toward integrated, multi-scale monitoring systems. Across the body of literature from 2012–2025, RS demonstrated a strong capability for the direct retrieval of optically active water quality parameters, including Chl-a, turbidity, TSS, CDOM, SDD, and surface water temperature. The evidence demonstrates that RS has progressed beyond a supplementary observational tool and now forms the backbone of spatially continuous environmental assessment. At the same time, the expansion of ML approaches has extended retrieval capabilities to parameters lacking direct optical signatures, though with increased demands for validation consistency and uncertainty transparency. GIS has proven necessary for spatial interpolation, watershed and catchment analysis, multi-criteria decision support, and integration of satellite-derived indicators with land use, hydrological, and climatic drivers.

Finally, the integration of the enhanced RS-GIS results with management metrics, pollution source tracing, water quality parameters, and policy decision tools is important to shift from proof-of-concept research towards continued operational monitoring. When supported by standardized workflows, uncertainty reporting, transparent calibration, and spatio-temporal validation practices, integrated RS–GIS systems can provide spatially explicit evidence suitable for structured decision-support processes in water-resource management. Addressing these gaps will enable the RS–GIS community to contribute to a more consistent, spatially explicit water quality monitoring that can inform environmental management and policy evaluation, subject to appropriate validation and uncertainty reporting.

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